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# Autonomous agent negotiation strategies in complex environments

Fenghui Ren  
University of Wollongong

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# Autonomous Agent Negotiation Strategies in Complex Environments

A thesis submitted in fulfillment of the  
requirements for the award of the degree

**Doctor of Philosophy**

from

UNIVERSITY OF WOLLONGONG

by

**Fenghui Ren**

School of Computer Science and Software Engineering  
April 2010



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by

Fenghui Ren

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*Dedicated to*  
*My family and friends*

# Declaration

This is to certify that the work reported in this thesis was done by the author, unless specified otherwise, and that no part of it has been submitted in a thesis to any other university or similar institution.

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Fenghui Ren  
April 30, 2010

# Abstract

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Autonomous agents are software agents that are self-contained, capable of making independent decisions, and taking actions to satisfy internal goals based upon their perceived environment. Agent negotiation is a means for autonomous agents to communicate and compromise to reach mutually beneficial agreements. By considering the complexity of negotiation environments, agent negotiation can be classified into three levels, which are the *Bilateral Negotiation Level*, the *Multilateral Negotiation Level*, and the *Multiple Related Negotiation Level*.

In the *Bilateral Negotiation Level*, negotiations are performed between only two agents. The challenges on this level are how to predict an opponent's negotiation behavior, and how to reach the optimal negotiation outcome when the negotiation environment becomes open and dynamic. The contribution of this thesis on this level is (1) to propose a regression-based approach to learn, analyze and predict the opponent negotiation behaviors in open and dynamic environments based on the historical records of the current negotiation; and (2) to propose a multi-issue negotiation approach to estimate the opponent's negotiation preference, and to search for the bi-beneficial negotiation outcome when the opponent changes its negotiation strategies dynamically.

In the *Multilateral Negotiation Level*, negotiations are performed among more than two agents. Agents need more efficient negotiation protocols, strategies and approaches to handle outside options as well as competitions. Especially when negotiation environments become open and dynamic, future possible upcoming outside options still need to be considered. The challenge in this level is how to guide agents to efficiently and effectively reach agreements in highly open and dynamic negotiation environments, such as e-marketplaces. The contribution of this thesis on this level is (1) to propose a negotiation partner selection approach to filter out unexpected negotiation opponents before a multilateral negotiation starts; (2) to extend

a market-driven strategy for multilateral single issue negotiation in dynamic environments by considering upcoming changes of the environment; and (3) to propose a market-based strategy for multilateral multi-issue negotiation by considering both markets situations and agents specifications.

In the *Multiple Related Negotiation Level*, several negotiations are processed together by agents in order to achieve a global goal. These negotiations are not absolutely independent, but some how related. In order to ensure the global goal can be efficiently achieved, factors such as the negotiation procedure, the success rate, and the expected utility for each of these related negotiations should be considered. The contribution of this thesis on this level is to introduce a Multi-Negotiation Network (MNN) and a Multi-Negotiation Influence Diagram (MNID) to search for the optimal policy to concurrently conduct the multiple related negotiation by considering both the joint success rate and the joint utility.

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# Publications

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The following is a list of my research papers that have been already published during my PhD study that ends with the completion of this thesis.

## Scholarly Book Chapters

- 1 **Fenghui Ren** and Minjie Zhang, Desire-Based Negotiation in Electronic Marketplaces. In *Post-Proceedings of the Second International Workshop on Agent-based Complex Automated Negotiations (ACAN09), Innovations of Agent-based Complex Automated Negotiations*, (accepted in Jan. 2010), in press.
- 2 John Fulcher, Minjie Zhang, Quan Bai and **Fenghui Ren**, Discovery of Telephone Call Patterns by the use of Intelligent Reasoning. In *K. Nakamatsu (Ed.), Handbook of Intelligent Reasoning*, World Scientific, (accepted in Oct. 2008).
- 3 Mingjie Zhang, Quan Bai, **Fenghui Ren** and John Fulcher, Chapter IV: Collaborative Agents for Complex Problem Solving. In *C. Mumford and L. Jain (Ed.), Computational Intelligence, Collaborative, Fusion and Emergence*, Springer, pp. 361-399, 2009.
- 4 Quan Bai, **Fenghui Ren**, Minjie Zhang and John Fulcher, Chapter 8: CPN-Based State Analysis and Prediction for Multi-Agent Scheduling and Planning. In *T. Ito, M. Zhang, V. Robu, S. Fatima and T. Matsuo (Ed.), Advances in Agent-Based Complex Automated Negotiation, Studies in Computational Intelligence*, Springer, Vol.233, pp. 161-176, 2009.
- 5 **Fenghui Ren** and Minjie Zhang, Chapter 12: The Prediction of Partners' Behaviors in Self-Interested Agents. In *M Yokoo, T. Ito, M. Zhang, J. Lee and T. Matsuo (Ed.), Electronic Commerce: Theory and Practice. Studies in Computational Intelligence*, Springer, Vol. 110, Springer, pp. 157-170, 2008.

## Refereed Journal Articles

- 6 **Fenghui Ren**, Minjie Zhang and Kwang Mong Sim, Adaptive Conceding Strategies for Automated Trading Agents in Dynamic, Open Markets. *Decision Support Systems*, Elsevier, Vol. 46, No. 3, pp. 704-716, 2009.
- 7 Quan Bai, **Fenghui Ren**, Minjie Zhang and John Fulcher, CPN-Based State Analysis and Prediction for Multi-Agent Scheduling and Planning. In *Multi-agent and Grid Systems, International Transactions on Systems Science and Applications*, (accepted in Dec. 2009), in press.
- 8 **Fenghui Ren**, Minjie Zhang and John Fulcher, Expectation on Behaviour of Trading Agent in Negotiation in Electronic Marketplace. *Web Intelligence and Agent Systems: An International Journal*, (accepted in Nov. 2009), in press.
- 9 **Fenghui Ren** and Minjie Zhang, Prediction of Partners Behaviors in Agent Negotiation under Open and Dynamic Environments. In *International Transactions on Systems Science and Applications*, Vol 4, No. 2, pp. 295-304, 2008.
- 10 **Fenghui Ren** and Minjie Zhang, Partners Selection in Multi-Agent Systems by Using Linear and Non-linear Approaches. In *Transactions on Computational Sciences I*, pp. 37-60, 2008.
- 11 **Fenghui Ren**, Minjie Zhang and Jun Yan, An Extended Dual Concern Model for Partner Selection in Multi-agent Systems. In *System and Information Sciences Notes*, Vol 1, No. 2, pp. 153-158, 2007.

## Refereed Conference Papers

- 12 **Fenghui Ren**, Minjie Zhang, Chunyan Miao and Zhiqi Shen, A Market-Based Multi-Issue Negotiation Model Considering Multiple Preferences in Dynamic E-Marketplaces. In *Proceedings of the 12th International Conference on Principles of Practice in Multi-Agent Systems (PRIMA09)*, pp. 1-16, 2009. (**Best Student Paper Award**)
- 13 **Fenghui Ren** and Minjie Zhang, Optimal Multi-Issue Negotiation in Open and Dynamic Environments. In *PRICAI2008: Trends in Artificial Intelligence, Lecture Notes in Artificial Intelligence, LNAI 5351*, pp. 321-332, 2008.



- 14 **Fenghui Ren**, Kwang Mong Sim and Minjie Zhang, Market-Driven Agents with Uncertain and Dynamic Outside Options. In *Proceedings of the Sixth International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS07)*, Honolulu, US, pp. 721-723, 2007.
- 15 **Fenghui Ren** and Minjie Zhang, Prediction Partners' Behaviours in Negotiation by Using Regression Analysis. In *Proceedings of the Second International Conference on Knowledge Science, Engineering and Management, Lecture Notes in Artificial Intelligence, LNAI 4798*, Springer, pp. 165-179, 2007, (**Runner-up, Best Student Paper Award**).
- 16 **Fenghui Ren**, Minjie Zhang and Quan Bai, A Fuzzy-Based Approach for Partner Selection in Multi-Agent Systems. In *Proceedings of the Sixth IEEE/ACIS International Conference on Computer and Information Science*, Melbourne, Australia, pp. 457-462, 2007.
- 17 Quan Bai, Minjie Zhang and **Fenghui Ren**, A Colored Petri Net Based Approach for Flexible Agent Interactions. In *Proceedings of the Fourth IEEE International Conference in IT and Application*, Harbin, China, pp. 186-191, 2007.
- 18 **Fenghui Ren** and Minjie Zhang, Prediction of Partners' Behaviors in Agent Negotiation under Open and Dynamic Environments. In *Proceedings of 2007 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology Workshops*, pp. 379-382, 2007.

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# Chapter 1

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## Introduction

Up to now, although no standard definition is accepted by all people as an explanation for an autonomous agent, a common understanding is that it can be realized as a software agent, is self-contained, capable of making independent decisions, and taking actions to satisfy internal goals based upon its perceived environment. A multi-agent system (MAS) is a system composed of multiple interacting agents. During the last decade, multi-agent systems (MASs) have experienced rapid growth in both techniques and applications, and become one of the most important and representative AI techniques. MASs have been widely applied in many fields, such as E-commerce, grid computing, decision support systems, and engineering [Woo02]. In a competitive MAS, agents may have different individual goals, and conflicts may appear. In a cooperative MAS, agents usually share a common goal, and conflicts may still happen during interactions when agents use different approaches, resources, and understanding to achieve the common goal. In order to solve conflicts during interactions, negotiation is introduced as a general mechanism to help agents achieve their individual and/or common goals.

Negotiation is a means for autonomous agents to communicate and compromise to reach mutually beneficial agreements when conflicts appear between them [FWJ04a, Kra01]. In general, agents can be characterized as self-interested agents [San96] and cooperative agents [Les99]. Agent negotiation plays an important role for both types of agent.

Commonly, a negotiation among self-interested agents is named *competitive negotiation* [GM98]. Agents in a *competitive negotiation* usually have different individual goals and interests in maximizing their own benefits. If an agent's goal in a *competitive negotiation* meets a conflict, normally the agent shows selfish behavior and will not sacrifice its benefit to help other agents to achieve their goals. Agent negotiation actualizes a mechanism for self-interested agents to make concessions on

their original goals so as to ensure partial achievements, but not absolute failure on their goals.

By contrast, agent negotiation among cooperative agents is usually named *cooperative negotiation* [MLH03]. Agents in a *cooperative negotiation* normally work together towards a common goal, and they always show cooperative behaviors to maximize the global benefit. For cooperative agents, even though they have a common goal, each agent may have different knowledge, understanding and approaches to achieve the common goal, conflicts may also happen. Agent negotiation provides a mechanism for cooperative agents to generate an agreement among them to efficiently achieve the common goal.

Nowadays, many MASs operate in complex, open and dynamic environments with different constructions and relationships among agents. Such an environment has brought new challenges for researchers to develop negotiation approaches and strategies in MASs. The purpose of this Ph.D study is to investigate these challenging problems in agent negotiation, and to develop new negotiation mechanisms to solve these challenges in more effective and efficient ways.

The organization of this chapter is as follows: Section 1.1 introduces a personal view of agent negotiation, and classifies agent negotiation approaches into three levels by considering the complexity of negotiation environments. Based on a three-level view, Section 1.2 introduces the main research topics covered in each level, and points out four major challenging problems in developing approaches of agent negotiation in complex environments. Section 1.3 gives the motivations of this thesis, and Section 1.4 presents the contributions of this thesis. Finally, Section 1.5 details the organization of this thesis.

## 1.1 A Personal View of Agents Negotiation

In this section, a personal view and a classification of agent negotiation are introduced. Usually, two key settings need to be considered when agent negotiation is discussed, ie. the *agent setting* and the *environment setting*. The *agent setting* indicates an agent's individual understanding and reactions in a negotiation, while the *environment setting* represents the whole negotiation environment shared by all participants. Different agents may have different *agent settings* for the negotiation with the same *environment setting*, and agents can also modify their *agent setting* for a negotiation when necessary. However, the *environment setting* is relatively

‘static’, and usually will be not modified once all negotiation participants reach consensus. This section introduces both the *agent setting* and the *environment setting*, and presents a classification of agent negotiation by considering the complexity of the *environment settings*.

### 1.1.1 *Agent Setting*

Normally, the *agent setting* of a negotiation consists of six factors, which are the *negotiation protocol*, *negotiation strategy*, *negotiation preference*, *negotiation procedure*, *negotiation equilibrium* and *information privacy*. These six factors are specified as follows.

#### 1. *Negotiation protocol*

A *negotiation protocol* specifies the rules of encounter in an agent negotiation. It defines what kinds of (1) interactions between agents can be taken under different circumstances; (2) offer sequences are allowed, and (3) deals can be made in the negotiation. Rubinstein’s alternating offer protocol is a very commonly used negotiation protocol [Rub82]. In Rubinstein’s protocol, two agents are involved in a negotiation. Either agent can start the negotiation with an initial offer, and waits for a response from the other agent. The opponent may respond by either accepting the offer, rejecting the offer, or opting itself out of the negotiation. If the opponent chooses to accept an offer, the negotiation is successful in reaching an agreement; if the opponent chooses to reject an offer, a counter-offer will be returned to the agent; and if the opponent chooses to opt out of the negotiation, then the negotiation will fail without reaching an agreement. Such a process is repeated until one possible ending is achieved. Besides Rubinstein’s protocol, others protocols may also be adopted in different situations [IHK07, HSLM07, End06]. However, no matter which negotiation protocol is adopted, agents should reach a consensus on the negotiation protocol before a negotiation starts.

#### 2. *Negotiation strategy*

A *negotiation strategy* specifies the sequence of actions that the negotiation participants plan to make during a negotiation. In a *competitive negotiation*, an agent is usually interested in maximizing its own benefit, and an individual negotiation goal may be considered prior to choosing a *negotiation strategy*.

For example, Fatima et al. [FWJ04a] proposed a NDF *negotiation strategy* for self-interested agents when the negotiation time is the crucial decision making factor. In a *cooperative negotiation*, agents work together toward a common goal, and the global benefit may become a signification consideration. For instance, Czajkowski et al. [CFK<sup>+</sup>02] proposed a SLA *negotiation strategy* for cooperative agents on resource allocation. It must be pointed out that a *negotiation strategy* which performs well with a certain *negotiation protocol* may not necessarily do so well with other *negotiation protocols*. Therefore, the *negotiation protocol* in use should be considered when agents choose their *negotiation strategies*.

### 3. Negotiation Preference

A *negotiation preference* indicates an agent's emphasis level on the negotiated issues when more than one negotiation issue is considered. Usually, a negotiation preference is represented linearly as a serial of weight values [FWJ04b], where each weight value indicates the agent's concern on a particular issue. The greater/lower the weight value assigned to an issue, the more/less concern will be paid to the issue. However, when an agent's preference cannot be represented as a linear relationship, a non-linear representation may also be adopted [IHK07, SP06].

### 4. Negotiation procedure

A *negotiation procedure* specifies how issues are settled in a negotiation when it contains more than one issue. Broadly speaking, *package deal procedure*, *simultaneous procedure*, and *sequential procedure* [FWJ06a] are three common procedures acknowledged by most researchers. Some hybrid negotiation procedures for special negotiation purposes are also proposed to improve both the effectiveness and efficiency of negotiations [DH05].

### 5. Negotiation equilibrium

A *negotiation equilibrium* indicates the stability of a negotiation. When agents choose the *negotiation protocol* and *negotiation strategy*, agents create negotiation mechanisms. During a negotiation, the negotiation mechanism must be stable, i.e. a strategy profile must constitute an equilibrium. The Nash equilibrium [Nas50b, Rub82] is a commonly used concept when a negotiation

agreement is discussed. If a negotiation is in Nash equilibrium, no negotiation participant can increase its individual benefit through unilaterally changing only its *negotiation strategy*. The *negotiation equilibrium* is a very important and necessary condition for a negotiation system to be stable. For different *negotiation protocols*, the *negotiation equilibrium* may be different. However, it is required that each agent should select an equilibrium strategy before a negotiation starts.

#### 6. *Information privacy*

An *information privacy* specifies the access authority for negotiation information, which is classified as the *private information* and the *public information* [FWJ04b, FWJ06b]. The *private information* indicates that negotiation information is only accessible by an individual agent, such as the *negotiation strategy* and the *negotiation procedure*, while the *public information* can be accessed by all negotiation participants. In a negotiation, if all negotiation participants would like to share their *private information*, then the negotiation is named a *complete information negotiation*. Otherwise, if any negotiation participant does not want to share its *private information*, then the negotiation is named a *incomplete information negotiation*. An agent's *information privacy* may impact its choice on the *negotiation strategy*.

Besides the above six factors, other factors which may indicate an agent's individual opinions and/or activities in a negotiation can also be added into an *agent setting*. However, an *agent setting* only describes possible situations that an agent may face during a negotiation and possible actions that the agent may perform under different situations. The real action that an agent may perform in a particular negotiation usually depends on the *environment setting* of the negotiation.

### 1.1.2 *Environment Setting*

The *environment setting* of a negotiation describes the objective situations of a negotiation environment, which may contain the factors *number of issues*, *number of participants*, *environment state*, and *multiple negotiation relationship*. The four factors for an *environment setting* are specified as follows.

#### 1. *Number of issues*



The *number of issues* indicates how many issues a negotiation contains. Based on this factor, agent negotiation can be classified as *single issue negotiation* [JFL<sup>+</sup>01] and *multiple issue negotiation* [FWJ02]. In a *single issue negotiation*, agents negotiate on just one attribute. The success or failure of the negotiation fully depends on whether an agreement can be reached on the only issue. Usually, the pie splitting model from Game Theory [FUP91] is employed to represent the negotiation process in *single issue negotiation*. By contrast, in a *multiple issue negotiation*, agents need to negotiate on several issues in order to achieve final agreement. So the negotiation result depends on agreements on each individual issue. Usually, *multiple issue negotiation* is more efficient than *single issue negotiation* by considering the speed of negotiations and the quality of negotiation outcomes. However, *multiple issue negotiation* requires a more complex *negotiation protocol* and a *negotiation strategy*.

## 2. Number of participants

The *number of participants* indicates how many participants a negotiation contains. Based on this factor, agent negotiation can be classified into *bilateral negotiation* [CI86] and *multilateral negotiation* [BR88]. A *bilateral negotiation* is only performed between two agents, and the negotiation will fail if an agreement cannot be reached between the only pair of participants. By contrast, a *multilateral negotiation* contains more than two agents. Agents may have outside options, and face competition from other competitors. If an agent fails to reach an agreement with one opponent, it still has a chance to reach agreements with other opponents. Usually, *multilateral negotiation* provides more chances for agents to reach agreement, but needs more complex *negotiation protocols* to deal with concurrent negotiation threads [LGS06] between each pair of participants.

## 3. Environment state

An *environment state* indicates the possible change of negotiation environments in the future. If there is no upcoming outside options entering into a negotiation in the future, the negotiation is called *static negotiation*, while if outside options may enter into the negotiation in the future, the negotiation is named *dynamic negotiation* [Sim02]. In contrast to a *static negotiation*, a *dynamic negotiation* is more difficult to handle. Agents usually need a prediction

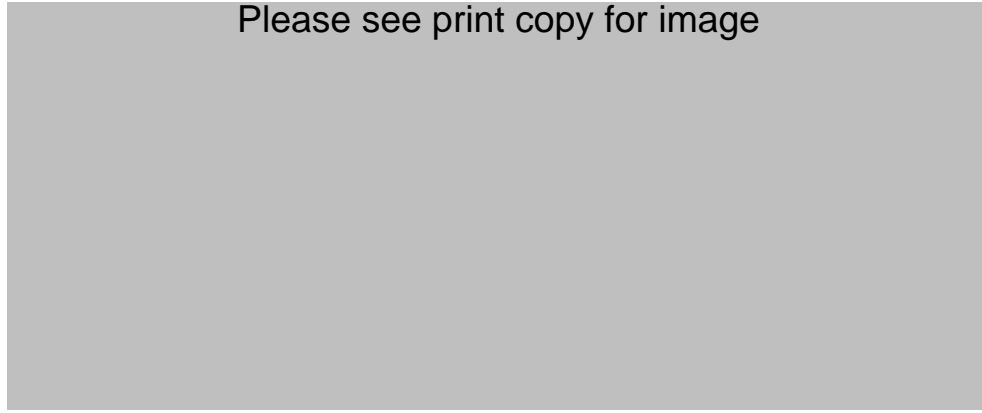


Figure 1.1: A nested view of general negotiation models [LS06].

mechanism to estimate future possible changes of negotiation environments in *dynamic negotiation*, so as to perform pre-actions to maximize negotiation outcomes.

#### 4. Multiple negotiation relationship

A *multiple negotiation relationship* indicates the relationship between individual negotiations. If the outcome of a negotiation does not depend on other negotiations, the negotiation is named *solo negotiation*. However, if the outcome of one negotiation depends on the outcomes of other negotiations, these negotiations are called *multiple related negotiations* [ZL02]. Usually, a *solo negotiation* is performed if the goal of the negotiation is independent, while a *multiple related negotiation* is performed when several dependent goals need to be achieved together.

### 1.1.3 A Classification of Agent Negotiation

Based on the personal view of agent negotiation introduced in the previous subsection, a classification of agent negotiation will be introduced in this subsection. However, before introducing our model, a famous classification model proposed by other researchers is firstly presented.

In Figure 1.1, Sycara et al. [LGS06] introduced a three-level nested view of agent negotiation. The first level in their model is named *single-threaded negotiations*, which represents static bilateral negotiations. The second level is *synchronized multi-threaded negotiations*, which represents static multilateral negotiations. And the third level is named *dynamic multi-threaded negotiations*, which represents dynamic multilateral negotiations. Since Sycara's model only considers *solo negotiation*, a

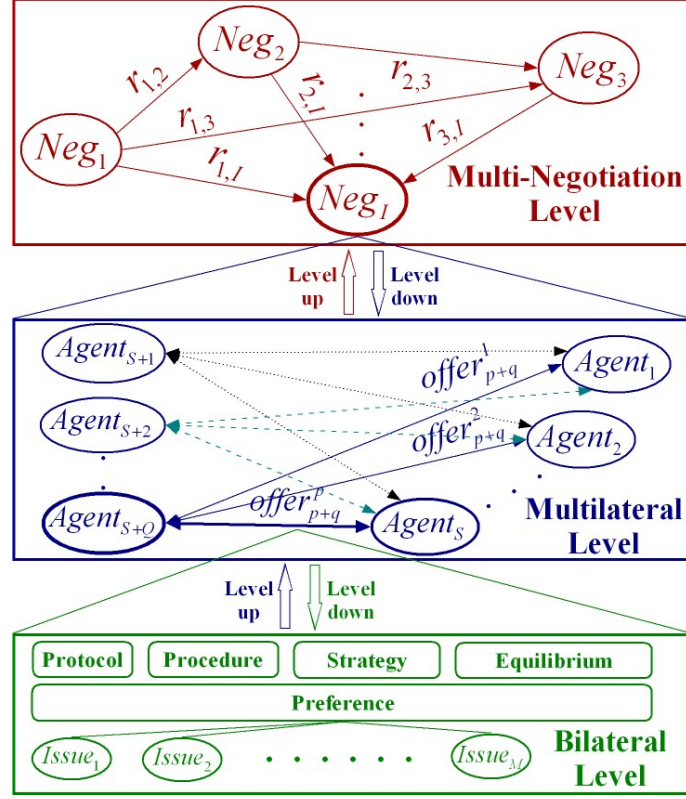


Figure 1.2: Three levels hierarchical view of agent negotiation.

new three-level hierarchical view is proposed in this thesis by including consideration of *multiple related negotiations* as shown in Figure 1.2.

Figure 1.2 classifies negotiation models based on the complexity of *environment settings* in agent negotiation, which contains a *Bilateral Level*, a *Multilateral Level*, and a *Multi-Negotiation Level*. Each level is specified as follows.

### 1. Bilateral Level

The first level is named the *Bilateral Level*, which covers static, bilateral negotiations. In this level, agents focus on sophisticated negotiation with only one opponent. In order to achieve an optimal negotiation outcome, agents may adopt different procedures [FWJ04a, FWJ06a], strategies [FSJ98, Kra01], equilibriums [Rub82] and preferences [FWJ07, FWJ09, MMLCVH09] based on their individual *agent settings*.

### 2. Multilateral Level

The second level is named the *Multilateral Level*, which covers dynamic, multilateral negotiations. In this level, agents negotiate with more than one opponent synchronously. Researchers on this level may pay attention to negotiation partner selections [BK05, WCD98], multilateral negotiation protocols [HSLM07, NJ04a], and negotiation strategies for open and dynamic environments [LGS06, RZS09].

Both the first and second levels focus on *solo negotiation*.

### 3. Multi-Negotiation Level

The third level is named the *Multi-Negotiation Level*, which pays attention to *multiple related negotiations*. Negotiations in this level are somehow related, and agents need to complete them all in order to achieve a final goal.

Each individual negotiation in the *Multi-Negotiation Level* could be an instance of either the *Bilateral Level* or the *Multilateral Level*.

In this section, both the *agent setting* and the *environment setting* of agent negotiation were introduced, and a three-level hierarchical view also introduced to represent negotiation models among autonomous agents within different complexity levels.

## 1.2 Research Issues and Challenges in Agent Negotiation

Although research in agent negotiation has resulted in significant advancements, some existing research issues have yet to be solved properly, and many new issues also emerged with the development of autonomous agents and MASs. In this section, research issues for agent negotiation at each level of the three-level hierarchical view are firstly discussed, then four major challenging problems are summarized based on these research issues.

### 1.2.1 Research Issues in Agent Negotiation

#### In the *Bilateral Level*

In the *Bilateral Level*, negotiations are processed between only two agents; research issues of this level include:

### 1. *Bilateral negotiation protocol*

A bilateral negotiation protocol is a basic research issue in agent negotiation, which specifies the rules of encounter in a negotiation between two agents. The major challenge of this research issue is how to improve the effectiveness and efficiency of a bilateral negotiation for both single and multiple issue negotiation when the negotiation environment becomes open and dynamic.

### 2. *Agent behavior prediction*

In agent negotiation, an agent will have a great advantage if the opponent's negotiation behaviors can be acquired by the agent. However, most opponents will not share their *private information* with other agents, which makes the negotiation process harder and inefficient. The major challenge of this research issue at the present time is how to effectively and efficiently predict an opponent's negotiation behaviors in open and dynamic environments, and how to improve the negotiation outcome by using the prediction results.

### 3. *Agent preference prediction*

In multiple issue negotiation, a 'win-win' negotiation outcome can be possibly achieved between two agents, which can benefit both negotiation participants. An agent's preference plays a crucial role in multiple issue negotiation when a mutually beneficial agreement is discussed. However, agents usually keep their preferences as *private information*, which increases the difficulty of reaching a mutually beneficial agreement for both participants. The major challenge of this research issue at the present time is how to effectively and efficiently predict an opponent's preference, and how to search for a 'win-win' negotiation outcome by employing the prediction results.

## **In the *Multilateral Level***

In the *Multilateral Level*, negotiations are processed between more than two agents with future possible upcoming outside options. Negotiation environments become unstable and uncertain, the research issues at this level may include:

### 1. *Multilateral negotiation protocol*

Multilateral negotiation protocol specifies the rules of encounter in negotiation between more than two agents. The major challenges of this research issue

at the present time include (1) how to synchronize the negotiation process between several opponents, (2) how to make a reasonable reaction based on all opponents' responses, and (3) how to generate suitable reactions by considering the unstability and uncertainty of the negotiation environment.

## 2. *Negotiation partner selection*

In multilateral negotiation, an agent may face many opponents. Usually, not all of these opponents have the potential to reach an agreement with the agent. For example, some opponents may suddenly leave off the negotiation midway; some opponents may be unqualified for the agent requirement; and some opponents might not have a potential agreement zone with the agent. Therefore, it is not necessary for the agent to perform a sophisticated negotiation with all opponents, and an agent can eliminate unnecessary opponents before a negotiation starts. The major challenge of this research issue at the present time is how to efficiently identify opponents who have a great potential to reach an agreement based on different criteria in an open and dynamic negotiation environment.

## 3. *Single issue negotiation in multilateral environment*

In an open and dynamic multilateral negotiation environment, agent negotiation strategies on single issue negotiation may need to consider outside options and future possible changes in the negotiation environment. The major challenge of this research issue at the present time is how to improve agent negotiation strategies in single issue negotiation by considering the impact of competition from competitors, as well as by considering the impact of opportunities from outside options. Also, future possible changes of the negotiation environment should be taken into account when upcoming outside options enter into the negotiation in the future.

## 4. *Multiple issue negotiation in multilateral environment*

An agent's preference on negotiated issues plays a significant role in determining whether a 'win-win' outcome can be achieved in a multiple issue negotiation. In an open and dynamic multilateral environment, opponents may modify their negotiation preferences when the negotiation environment changes. Some agents may even have several negotiation preferences at the same time,

and present different preferences when facing different negotiation opponents. The major challenge of this research issue at the present time is how to employ multiple preferences on different issues in an open and dynamic multilateral environment to increase agents' opportunities for reaching a mutually beneficial agreement.

### **In the *Multi-Negotiation Level***

In the *Multi-Negotiation Level*, negotiations are somehow related. If agents fail one negotiation, other related negotiations may also be impacted. Therefore, these multiple related negotiations should be considered relatively. The research issues in this level include:

#### *1. Multiple related negotiation procedure*

Multiple related negotiation can be performed sequentially, or concurrently, or based on a hybrid procedure by combining the previous two procedures. The major challenge of this research issue at the present time is how to decide an appropriate procedure for agents when multiple related negotiations need to be performed with different *environment settings*.

#### *2. Multiple related negotiation optimization*

In multiple related negotiations, agents' actions and/or agreements for one negotiation may impact other related negotiations. Therefore, in order to optimize the outcome for all related negotiations, a negotiation strategy should be invented to instruct agents to optimally perform and synchronize their negotiation behaviors between related negotiations. The major challenge of this research issue at the present time is how to dynamically determine a decision policy for agents in multiple related negotiations to optimize the negotiation outcome.

## **1.2.2 Four Major Challenging Problems in Agent Negotiation**

Based on the research issues discussed in the previous subsection, four major challenging problems which might occur in different levels in agent negotiation are summarized in this subsection. These four major challenging problems are:

### 1. *Different criteria on negotiation issues*

In multiple issue negotiation, agents may have different preferences and expectations on different issues, and different criteria might be used to evaluate different issues [LJS<sup>+</sup>03]. How to efficiently and effectively reach an optimal negotiation outcome among agents by considering different criteria becomes a very challenging problem in agent negotiation.

### 2. *Multiple participants involving negotiation*

A complex MAS may contain many individual agents nowadays. When a conflict happens in such a MAS with multiple participants, in order to achieve an optimal agreement, an agent may need to negotiate with more than one opponent at the same time. Obviously, the traditional one-to-one negotiation (bilateral negotiation) is not powerful enough to handle such situations; multilateral negotiation is needed to overcome this limitation. How to efficiently and effectively reach an agreement in multilateral negotiation is another challenging problem in agent negotiation.

### 3. *Unstable and uncertain negotiation environment*

When the negotiation environment becomes open and dynamic, such as on the Internet, agents are not isolated from the outside world anymore, but can freely acquire information and communicate with other agents without considering the geographical limitations. An agent can also freely join or leave a negotiation midway, which makes the negotiation environment become more “unstable” and “uncertain”. The traditional negotiation mechanisms designed for a “static” and “certain” negotiation environment cannot handle such a new requirement anymore. Therefore, how to efficiently and effectively reach an agreement in an open and dynamic environment is the third challenging problem in agent negotiation.

### 4. *Optimization of Multiple Related Negotiation*

An agent may need to perform several negotiations in order to finally achieve a global goal. Sometimes, these multiple negotiations are not absolutely independent, but somehow related. An unsuccessful negotiation on any one of these related negotiations may lead to failure or damage to the global goal. Most existing approaches sequentially process these related negotiations, and have



difficulty in producing optimal outcomes for achieving global goals. Therefore, how to efficiently and effectively process multiple related negotiations in order to optimize the global outcome is the fourth challenging problem in agent negotiation.

In this section, several research issues were discussed for each level in the three-level hierarchical model based on the complexity of *environment settings*. To summarize these research issues, four major challenging problems in agent negotiation were further introduced.

### 1.3 Motivation of the Thesis

Based on the four major challenging problems summarized in the previous subsection, the motivations of this thesis are described as follows.

1. *To Predict Agent behavior in bilateral single issue negotiation*

In single issue negotiation, prediction of the opponent's negotiation behaviors is a significant research problem. The prediction results can be employed by agents as references to guide their decision making during negotiation behaviors. An accurate prediction result definitely can help agents to increase their negotiation outcomes. Bayesian learning and machine learning approaches are widely used to solve the agent behavior prediction problem. However, both of them have disadvantages. Bayesian-learning-based approaches usually require prior domain knowledge and prior hypothesis to calculate the posterior probability for the hypothesis, but this information may not be available in some circumstances. Machine-learning-based approaches usually need pre-processing to train agents, but no training algorithm can guarantee that an agent will be trained perfectly. If an opponent's behavior is not included in the training dataset, the prediction result may not be accurate. The first motivation of this thesis is to provide solutions to overcome the limitations of Bayesian learning and machine learning approaches in agent behavior prediction in bilateral single issue negotiation.

2. *To optimize outcomes in bilateral multiple issue negotiation*

Multiple issue negotiation has become an active research topic in recent years. By comparison with single issue negotiation, the major advantage of multiple issue negotiation is that a ‘win-win’ negotiation outcome can be found to benefit both negotiation participants, which cannot be achieved in single issue negotiation. An agent’s preference on negotiated issues in multiple issue negotiation is a significant factor in searching such a mutually beneficial agreement. The second motivation of this thesis is to propose an agent preference prediction approach and an optimization method to help agents reach the mutually beneficial negotiation outcome in bilateral multiple issue negotiation.

3. *To select partner in multilateral negotiation*

In multilateral negotiations, agents need to face more than one opponent. Especially when a negotiation environment becomes open and dynamic, existing opponents can leave off the negotiation midway and a new opponent can enter the negotiation freely as well. In this case, it is almost impossible and also unnecessary for agents to perform a sophisticated negotiation with each opponent. Some opponents which do not have the potential to reach an agreement with the agent can be eliminated before a negotiation starts. The third motivation of this thesis is to develop a partner selection approach to eliminate unqualified opponents from potential partners so as to improve the efficiency of multilateral negotiations.

4. *To handle multilateral single issue negotiation*

When the negotiation environment becomes open and dynamic, agents will get more opportunities to reach an agreement, and also will face more competition from other competitors. The fourth motivation of this thesis is to propose a negotiation approach for efficiently handling multilateral single issue negotiation by considering future possible changes on negotiation environments, ie. number of outside options, number of competitors, and opponents’ negotiation strategies.

5. *To handle multilateral multiple issue negotiation*

In order to reach a mutually beneficial agreement in multilateral multiple issue negotiation, agents may have different preferences when they perform negotiations with different opponents. The fifth motivation of this thesis is to

propose a negotiation approach for multilateral multiple issue negotiation by considering a complex *environment setting* and multiple preferences.

6. *To optimize multiple related negotiation outcome*

In the real world, agents may need to perform several negotiations in order to reach a global goal. Usually, these negotiations are somehow related. Most existing approaches just perform multiple related negotiations sequentially. Because the result of the latter negotiation is not predictable by using a sequential procedure, agents cannot optimally execute all related negotiations in sequential order. In some cases, when the final goal of related negotiations cannot be reached, the former performed negotiations may become meaningless and agreements on these negotiations may lead to unnecessary losses. The sixth motivation of this thesis is to propose an approach to concurrently and optimally handle multiple related negotiations.

## 1.4 Contribution of the Thesis

Based on the motivations introduced in the previous section, six major contributions are achieved in this thesis, which are:

1. An agent behavior prediction approach is proposed to estimate opponents negotiation behaviors for bilateral single issue negotiation in dynamic negotiation environments.

A regression-based approach is proposed in this thesis to perform an efficient and accurate prediction of opponents behaviors. The proposed prediction approach includes three regression algorithms, ie. a linear regression algorithm, a quadratic regression algorithm and a power regression algorithm, based only on the historical offers of the current negotiation without a training process. Therefore, both efficiency and accuracy of prediction can be guaranteed. Each regression algorithm has both advantage and disadvantage. Agents can choose any algorithm during negotiations according to their negotiation specification and requirements.

2. An agent preference prediction approach and an optimization approach are developed to estimate the opponent's preference and to search for the mutually

beneficial negotiation outcome (if it is applicable) for bilateral multiple issue negotiation in dynamic negotiation environments.

The proposed preference prediction approach is based on the extension of a quadratic regression function. By employing the prediction approach, the opponent's preference can be efficiently estimated. The proposed optimization approach contains an algebraic algorithm and a geometric algorithm. The algebraic algorithm is good at handling negotiations with more than two negotiated issues, and the geometric algorithm is good at representing the optimization problem as a graph. Agents can choose any algorithm during negotiations according to their *agent settings*. Both algorithms can lead a multiple issue negotiation to a 'win-win' outcome (if applicable).

3. A negotiation partner selection approach is proposed in advance of multilateral negotiations to filter out unqualified opponents according to the agent's selection criteria.

The proposed partner selection approach contains a linear selection algorithm and a non-linear selection algorithm. The linear selection algorithm is easily implemented and can generate satisfactory selection results. The non-linear selection algorithm is a supplement for the linear selection algorithm, and can handle situations when the selection criteria cannot be represented linearly. Agents can choose either algorithm during negotiations according to their *agent settings* and selection criteria.

4. A market-driven-based negotiation approach is proposed to handle multilateral single issue negotiation in open and dynamic environments.

The proposed approach considers possible changes of factors of negotiation opportunities, negotiation competitions, negotiation strategies and negotiation eagerness for single issue negotiation when the negotiation environment becomes open and dynamic. Both the current and future possible situations of the negotiation environment are considered in the proposed approach. Agents can employ the proposed approach in dynamic negotiation environments to perform efficient negotiations.

5. A market-based negotiation approach and a multiple preference strategy are proposed to handle multilateral multiple issue negotiation in open and dynamic environments.

In order to increase the success rate of negotiations in a complex environment, the relationship between supply and demand is considered. The proposed market-based approach can monitor changes in the negotiation environment, and help agents to make more appropriate reactions in negotiation when the negotiation environment changes. Also, the proposed multiple preference strategy greatly increases an agent's opportunity for reaching a mutually beneficial agreement when it faces opponents with different preferences in dynamic, multilateral and multiple issue negotiations.

6. A Multi-Negotiation Network (MNN) and a Multi-Negotiation Influence Diagram (MNID) are proposed to concurrently and optimally handle multiple related negotiations.

In the proposed approaches, the joint success rate and the joint utility of all related negotiations are considered in deciding the policy for optimally conducting a multiple related negotiation. An agent's possible decision on each related negotiation is considered and reflected by the value of expected utility. The optimal policy is generated through comparing expected utilities between all possible policies so as to optimize the outcome of multiple related negotiations.

## 1.5 Organization of the Thesis

In this thesis, each chapter starts with an introduction and concludes with a summary.

**Chapter 1** introduces backgrounds of agent negotiation, challenging problems in agent negotiation, motivations of this thesis, and contributions of this thesis.

**Chapter 2** is a literature review of the key concepts and current research in agent negotiation based on a three-level hierarchical model. Research issues of bilateral single issue negotiation, bilateral multiple issue negotiation, negotiation pattern selection, multilateral single issue negotiation, multilateral multiple issue negotiation, and multiple related negotiations are discussed.

**Chapter 3** introduces an agent's behavior prediction approach for bilateral single issue negotiation. Three regression algorithms, ie. a linear regression algorithm, a quadratic regression algorithm, and a power regression algorithm, are

proposed for predicting opponents behaviors under different situations.

**Chapter 4** introduces an optimization approach for bilateral multiple issue negotiation. Firstly, based on the historical offers, a prediction algorithm is proposed based on the extension of a quadratic regression function to predict the opponent's preference. Then an algebraic algorithm and a geometric optimization algorithm are introduced to search for a mutually beneficial agreement for both negotiation participants.

**Chapter 5** introduces a negotiation partner selection approach by using a linear algorithm and a non-linear algorithm. Based on considerations of how likely an agreement can be reached with an opponent, opponents which do not satisfy agents specifications or unlikely to reach agreement are eliminated from potential negotiation partners before a multilateral negotiation starts.

**Chapter 6** introduces a market-driven negotiation approach for multilateral single issue negotiation in open and dynamic environments. Four concession factors are considered in open and dynamic e-market environments to help agents make efficient reactions in negotiations.

**Chapter 7** introduces a market-based negotiation approach for multilateral multiple issue negotiation in open and dynamic environments. Both the negotiation environment and the agent's negotiation expectation are considered. Also, a multiple preference strategy is proposed to increase the agent's opportunity in reaching a mutually beneficial agreement with opponents.

**Chapter 8** introduces an approach to perform multiple related negotiations concurrently and optimally. A Multi-Negotiation Network and a Multi-Negotiation Influence Diagram are proposed in this approach. The optimal policy for negotiation procedure is generated by considering both the success rate and the payoff of all related negotiations.

**Chapter 9** provides a summary of this thesis, and indicates further problems which could provide the basis for future research work.

# Chapter 2

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## Literature Review

### 2.1 Introduction

The complexity of agent negotiation is increased along with the changes of a negotiation environment. The simplest negotiation is processed between only two agents. They negotiate on only one issue, and share their *private information*, such as initial offers, reservation offers and deadlines, between each other. This type of negotiation is named bilateral single issue negotiation with complete information [MW95]. However, this type of negotiation is more like a theoretical model than a real world agent negotiation mechanism, since in reality most agents would not like to share their *private information* with others in the real world. In order to bridge this gap, negotiation approaches which can be applied within incomplete information settings are proposed for bilateral single issue negotiation [CS83]. A typical instance of this types of negotiation is the bargaining problem between a buyer and a seller over the price of an item. Both agents have different initial prices, reservation prices, negotiation strategies, and negotiation deadlines. This information is kept by each agent as *private information*, and agents will process the negotiation according to these predefined parameters.

In order to solve a complex task, sometimes agents need to consider multiple criteria during their interactions. If a conflict happens, agents usually need to take several factors into account during the negotiation before an agreement can be made for solving the conflict. Since single issue negotiation cannot handle the situation when multiple factors need to be considered; bilateral multiple issue negotiation has been invented by researchers to take multiple issues into account when a negotiation involves multiple criteria [FWJ02, LJS<sup>+</sup>03, FWJ04a]. By using such a negotiation mechanism, two agents can effectively and efficiently handle complicated conflicts during interactions between them.

When a conflict involves more than two agents, bilateral negotiation does not work. This limitation definitely impacts on the performance of a MAS when an agreement needs to be accepted by several agents. In order to solve such a problem, some multilateral negotiation mechanisms have been proposed by researchers [BR88, Wal90, KC03]. In a multilateral negotiation, agents could synchronously negotiate with several opponents, which greatly increases the chance for agents to reach an agreement in a MAS.

In the last decade, as the rapid development of information technology, especially the communication technology and the Internet, agents are not isolated from the outside world. Through the Intranet and/or Internet, agents can easily acquire information/services from remote resources, communicate with other agents located in remote areas, and supply information/services to other remote enquiries. The static structure of MASs is replaced by a dynamic structure, and agents can easily generate, dismiss, join, or leave a MAS. By comparison with the traditional static MASs, MASs in the current stage are more open and dynamic. In such a highly complex environment, it is more likely that conflicts may happen between agents. Furthermore, the uncertainty of future possible environments makes the agent negotiation more challenging. In order to meet these new requirements, agent negotiation in open and dynamic environments has become a very challenging and important topic in the area of MASs [LGS06, MLH03, FWJ07].

Besides agent negotiation in open and dynamic environments, another research topic which studies the relationships between multiple negotiations has also become an important topic in recent years [ZPL00, RZL00, ZL02]. The motivation of this research is derived from the fact that in a MAS, agents usually need to perform several negotiations with different opponents in order to achieve a final goal, and these multiple negotiations are not absolutely independent, but somehow related. Investigations on this topic at the current time focus on the negotiation procedure on multiple related negotiations, as well as the optimization of such negotiations.

There are many negotiation mechanisms proposed or developed by prior researchers, which might be applied under different circumstances. In this chapter, some related work about negotiation strategies, protocols, and models is investigated and studied based on the three-level hierarchical view introduced in Chapter 1, ie. the *Bilateral Level*, the *Multilateral Level*, and the *Multi-Negotiation Level*. Also, through comparisons and discussions of these negotiation mechanisms in different levels, the limitations of existing approaches will be pointed out, which show the



significance of this Ph.D study.

The organization of this chapter is as follows: Section 2.2 reviews and investigates negotiation mechanisms in the *Bilateral Level*, which includes both bilateral single issue negotiation and bilateral multi-issue negotiation. Section 2.3 reviews and investigates negotiation mechanisms in the *Multilateral Level*, which includes both static and dynamic multilateral environments. Section 2.4 reviews and investigates negotiation mechanisms in the *Multi-Negotiation Level*, which includes the procedure and optimization of multiple related negotiation. Finally, Section 2.5 summarizes this chapter and clarifies the significance of this thesis.

## 2.2 Bilateral Level

In this section, bilateral negotiation mechanisms are reviewed and discussed, which includes both bilateral single issue negotiation and bilateral multiple issue negotiation.

### 2.2.1 Bilateral Single Issue Negotiation

#### **with complete information**

A general bilateral single issue negotiation with complete information can be represented by the following case. Two agents, a buyer agent and a seller agent, negotiate on the price of an item. Each agent knows the *public information* of the negotiation environment, as well as the *private information* of its opponent, which may include the negotiation protocol, negotiation equilibrium, initial price, reservation price, negotiation strategy, and negotiation deadline. During the negotiation, agents exchange their offers in each negotiation round by using the alternating offer protocol [OR94]. The negotiation is successful when an agreement is reached between the two agents. Otherwise, the negotiation fails. Because each agent already knows the complete information about the negotiation, each agent should make its best response to the other agent in order to maximize the utilities for both of them. If an agent tries to increase itself's utility through diminishing the other's utility, such a behavior will definitely not be accepted by the other agent because the other agent is requested to make more concession than it should. Finally, when neither agent can make a further offer, which may increase its own utility without decreasing the

other's utility, an Nash equilibrium is achieved [Nas50a, Nas51]. In bilateral single issue negotiation with complete information, the Nash equilibrium is the agreement.

### with incomplete information

However, not all agents would like to share their *private negotiation* with their opponents in a real world negotiation, especially for self-interested agents. In such a case, each agent only knows its own negotiation parameters and the *public information*, but without knowing the other agent's *private information*. Agents cannot perform a reaction during negotiations by considering both negotiation participators, just by taking their own expectations into account.

A typical negotiation strategy in incomplete information settings was proposed by Faratin, Sierra and Jennings in [FSJ98], which uses time as a decision factor to determine an agent's concession during a negotiation. In such a time-based strategy, an agent usually starts a negotiation with its initial offer, and ends the negotiation at the deadline by offering its reservation offer. Theoretically, agents can have infinite possibilities for generating an offer between the initial offer and the reservation offer during the negotiation. However, in order to ensure the efficiency and stability of a negotiation, three typical behaviors are commonly employed by agents (see Figure 2.1), which are *Conceder*, *Boulware*, and *Linear*.

- *Conceder* represents a negotiation behavior that an agent will give larger concessions during the early stages of a negotiation, but smaller concessions during the later stages of the negotiation.
- *Linear* represents a negotiation behavior that an agent will give a constant concession throughout a negotiation.
- *Boulware* represents a negotiation behavior that an agent will give smaller concessions during the early stages of a negotiation, but larger concessions during the later stages of the negotiation.

Agents may employ other factors in determining its negotiation strategies based on different considerations and specifications of a negotiation. Besides the time-based strategy, resource-based and behavior-based strategies may also be employed by agents [FSJ98]. In a resource-based negotiation strategy, agents will make concessions based on the amount of available resources [CFK<sup>+</sup>02], and in a behavior-based

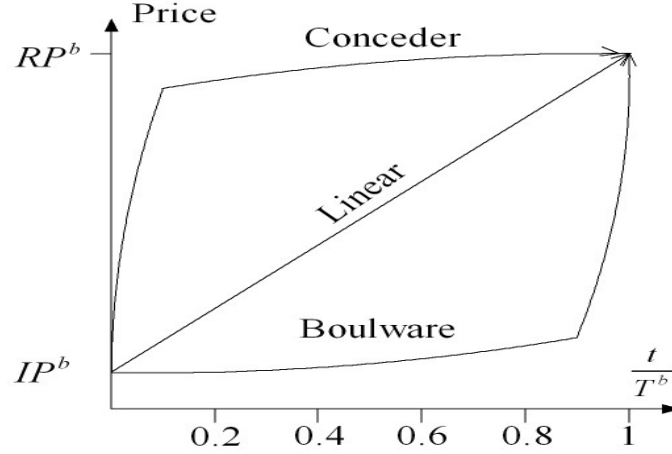


Figure 2.1: Negotiation decision functions for the buyer.

negotiation strategy, agents will make concessions based on the negotiation behaviors of its opponent [PRR01].

Because in an incomplete information setting, agents do not have their opponent's *private information*, the equilibrium is much harder to be achieved than in a complete information setting. In order to help agents to efficiently reach an agreement in an incomplete information setting, different approaches are proposed to predict the opponent's *private information*.

### Agent Behavior Prediction

In complete information settings, agents share all information with opponents, and the negotiation equilibrium can be reached effectively. But in an incomplete information setting, private negotiation parameters, such as the reservation offer, deadline and negotiation strategy are kept by agents in confidence. The negotiation equilibrium is usually harder to reach in incomplete information settings. Evidence from both theoretical analysis and real world observations suggest that for cooperative agents, if an agent can make a prediction on its opponent's negotiation behavior, it will be much easier for them to reach an agreement. For self-interested agents, if the opponent's negotiation behavior can be predicted during interactions, a self-interested agent will have a greater chance to increase its own utility. Therefore, in order to help cooperative agents to efficiently reach an agreement, as well as to help self-interested agents to maximize their utilities, agents should have an ability to learn from their opponent's historical negotiation behaviors, and to predict their opponent's possible negotiation behaviors in the future. In this subsection, we

review and compare some agent behavior prediction approaches.

In [ZS98, ZS97], D. Zeng and K. Sycara introduced a sequential decision making model to predict an opponent's reservation price, named Bazaar. Bazaar employs Bayesian learning to update the knowledge and belief that each agent has about the environment and other agents. The learning process is based on the prior knowledge of the negotiation domain and the agent's hypotheses on the opponent's reservation price, then a posterior probability to verify that the agent's hypotheses could be estimated. Through comparing all posterior probabilities for all hypotheses on the opponent's reservation price, the most likely reservation price for the opponent can be estimated. However, in the cases of (1) prior knowledge of the negotiation domain not being available for the agent, and (2) the agent not presenting reasonable hypotheses on the opponent's reservation price, this approach will fail to estimate the opponent's reservation price.

In [NJ05, NJ06], V. Narayanan and N. Jennings adopted a Markov chain framework to model bilateral negotiations and employed Bayesian learning to enable agents to learn an optimal strategy in incomplete information settings. The main purpose of this framework is to learn a mixed-strategy profile of an opponent and determine a strategy in response to this profile that maximizes an agent's pay-off at each stage of the negotiation process. Because the agent has no information about its opponent's negotiation strategy, a non-stationary Markov chain is used. Firstly, a state space including all possible strategies that the opponent may employ is constructed. Then the probability that the opponent will employ a particular strategy at each negotiation round is calculated. During negotiation, based on historical offers from the opponent, the probabilities that each negotiation strategy may be adopted by the opponent are dynamically updated. Finally, by comparing these probabilities, the strategy employed by the opponent can be estimated. The shortcomings of this approach are that (1) an agent needs special knowledge to construct a reasonable state space; and (2) an agent needs a strong computation ability to dynamically update the probability matrix for each potential strategy in each negotiation step.

In [BK06], J. Brzostowski and R. Kowalczyk proposed an approach to predict the opponent's behaviors based only on the historical offers of the current negotiation. The authors claimed that time and imitation are two main factors which influence an opponent's behaviors during negotiation. This approach allows an opponent to adopt either a time-dependant strategy or a behavior-dependant strategy.

Firstly, this approach needs to determine whether a time-dependant strategy or a behavior-dependent strategy is employed by the opponent. In order to achieve this, the differences between each two conjoint offers in the opponent's historical offers are calculated. If all the differences have the same sign (ie. all positive or all negative), then there are more chances for the opponent to adopt the time-dependant strategy. Otherwise, the opponent will have most likely adopt the behavior-dependent strategy. In order to determine the opponent's negotiation parameter for time-dependant strategy, (Conceder, Linear or Boulware), the sum of differences for each order for the opponent's historical offers is calculated. In order to determine the opponent's behavior for the behavior-dependant strategy, the differences between the agent's offers and the opponent's offers in each negotiation round are compared. Eventually, the opponent's negotiation strategy can be estimated. The shortcoming of this approach is the assumption that a time-dependant opponent should make monotonous concessions during the negotiation. However, such an assumption is not always true in real world negotiations.

In [FWJ04a], S. Fatima, M. Wooldridge and N. Jennings investigated negotiation outcomes in incomplete information settings through a comparison of the difference between two agent's negotiation deadlines, and proposed an agenda-based framework to help self-interested agents to maximize their utilities. This approach is based on an assumption that both agents use a time-dependent strategy, and can deliver their reservation offers at their deadlines. Since both agents do not know the other's deadline, they need to make a prediction of the opponent's deadline through observing the opponent's negotiation behaviors. If an agent estimates that its opponent's deadline is earlier than its own, then the agent can wait for the opponent's reservation offer. If the agent estimates that the opponent's deadline is later than its own, the agent should manage its negotiation behavior in order to avoid a failure. This approach presents a straightforward way for agents to adjust their negotiation behaviors based on the estimation results on the opponent's negotiation deadlines, but fails to consider that the opponent may adjust its behaviors during a negotiation.

Chajewska et al. [CKO01] proposed a decision-tree approach to learning and estimating an opponent's utility function. The authors assumed that each agent is rational and self-interested, and only interested in maximizing its own utility. Firstly, a decision tree is established which contains all possible endings for a negotiation, and each possible ending is assigned a particular utility value and possibility.

Based on the opponent's previous decisions in the decision tree, a linear function is generated analogous to the opponent's utility function. However, such an estimation approach has two shortcomings: (1) if an opponent's utility function is a non-linear function, such as a discrete function, this estimation approach will not work well; and (2) if an agent misses some possible negotiation endings before generating the decision tree, the accuracy of the estimation result may be decreased.

In [GP06], Gal and Pfeffer presented a machine learning approach to predict the opponent's negotiation behaviors based on a statistical method. Firstly, the proposed approach is trained by using records of different types of negotiation behaviors. Then an opponent's negotiation behavior is compared with the existing records. If the opponent's negotiation behavior matches any existing record, then the type of the opponent's negotiation behavior can be confirmed. Otherwise, the type of the opponent's negotiation behavior will be represented as a combination of some existing negotiation behaviors. The shortcoming of this approach is that the performance of the estimation approach depends on the training result. If the system cannot be trained by sufficient data to cover all types of behaviors, the performance of the estimation result would be poor.

In this subsection, we reviewed and investigated related work in bilateral single issue negotiation. Firstly, it is pointed out that a real world negotiation is often processed in an incomplete information setting, and agents do not have knowledge about an opponent's *private information*. In order to efficiently reach an agreement, agents need to be able to estimate the opponent's negotiation behaviors. Bayesian learning [ZS98, ZS97, NJ05, NJ06, BK06] is one of the most popular mechanisms to achieve such prediction. However, bayesian-learning-based approaches usually require prior knowledge about the negotiation domain and reasonable hypotheses for the possible results, which may limit their application in real world negotiations. Also, agenda-based [FWJ04a], decision-tree-based [CKO01], and machine-learning-based approaches [GP06] have been proposed by researchers to predict opponents' behaviors. However, agent-based approaches may have problems when an opponent dynamically modifies its negotiation behaviors; decision-tree-based approaches may have problems when the opponent's utility function cannot be represented linearly; and the machine-learning-based approaches may have problems when training data is not sufficient. In order to solve these problems, a regression-based approach is proposed in Chapter 3 to predict the opponent's negotiation behaviors just based on the opponent's historical offers in the current negotiation.

### 2.2.2 Bilateral Multiple Issue Negotiation

Multiple issue negotiation has become an important research topic during the last decade. By comparison with single issue negotiation, multiple issue negotiation has three major advantages, which are that (1) in real world applications, negotiations between people or businesses usually include many criteria, and these multiple criteria are almost impossible to be negotiated in a single issue negotiation; (2) multiple issue negotiation is more efficient than single issue negotiation because several attributes can be handled together; and (3) it is almost impossible to achieve an agreement to benefit both negotiation participators in single issue negotiation. Because agents may have different preferences in multiple issue negotiation, it is possible that a bi-beneficial negotiation agreement can be achieved. In this subsection, the basic approaches and procedures for multiple issue negotiation are reviewed. Some related work for searching the bi-beneficial negotiation outcome is investigated and discussed.

#### Negotiation Procedure

A bilateral multiple issue negotiation is processed between two agents. The negotiation contains more than one issue. For each issue, each agent usually has an initial offer and a reservation offer to indicate the range of acceptable values. Also, each agent has a preference to indicate its concerns on all negotiated issues. An agent's preference is usually represented linearly as a series of weights. During the negotiation, an agent may adopt different negotiation procedures to process the issues, and make decisions for the following actions by considering the evaluations on all issues. For instance, in a time-dependant strategy, if an agent's counter-offer cannot bring more utility than an opponent's offer in the next negotiation round, the agent will accept the opponent's offer and an agreement is achieved. Otherwise, the opponent's offer will be rejected and the counter-offer will be sent back to the opponent. This process is repeated until either an agreement is reached or one participator quits the negotiation. If any participator quits the negotiation without an agreement, the negotiation fails.

Because multiple issue negotiation has several issues to be negotiated, the negotiation procedure between single issue negotiation and multiple issue negotiation differs greatly. In general, there are three typical procedures in multiple issue negotiation, which are the *sequential procedure*, the *simultaneous procedure*, and the

*package deal procedure* [FWJ02, FWJ06b]. Each negotiation procedure defines an order to process the negotiated issues.

- By using the *sequential procedure*, issues in a multiple issue negotiation are negotiated sequentially, one after another. A *Sequential procedure* is also named as *issue-by-issue procedure*. In a *sequential procedure*, once bargaining on an issue is completed, the negotiation outcome for this issue is fixed. The later started negotiations on remaining issues may be impacted by the outcomes of pervious negotiations, but cannot change the outcomes of pervious negotiations. The *sequential procedure* is usually employed when the relationship between negotiated issues is not absolutely independent. Therefore, while one issue is being negotiated, the negotiation outcomes of completed issues can be considered.
- By using the *simultaneous procedure*, issues in a multiple issue negotiation are negotiated simultaneously, but independently. The difference between the *simultaneous procedure* and the *sequential procedure* is that the *sequential procedure* processes one issue at a time, and all issues are processed in a sequential order, while the *simultaneous procedure* processes all issues together. Usually, the *simultaneous procedure* is employed when the relationships between negotiated issues are absolutely independent.
- In contrast to the previous two procedures, in the *package deal procedure*, issues are negotiated simultaneously as a bundle. The bundled offer from an agent to an opponent is a package, which includes all sub-offers for each individual issue. The agent can choose either accepting the whole offer package, or rejecting the whole offer package, but cannot only accept some sub-offers in the package and reject the other sub-offers in the package. The *package deal procedure* is suitable for negotiating dependant issues simultaneously.

In order to compare the performance of the three negotiation procedures, Fatima, Wooldridge and Jennings [FWJ06a] suggested four criteria to judge the negotiation outcomes by employing these procedures, which are (1) time of agreement, (2) time to compute equilibrium, (3) pareto optimal, and (4) unique equilibrium. Generally, criteria (1) and (2) evaluate the efficiency of each procedure, and criteria (3) and (4) evaluate the effectiveness of each procedure. If a negotiation agreement is in equilibrium, then no agent can increase its payoff by changing its negotiation



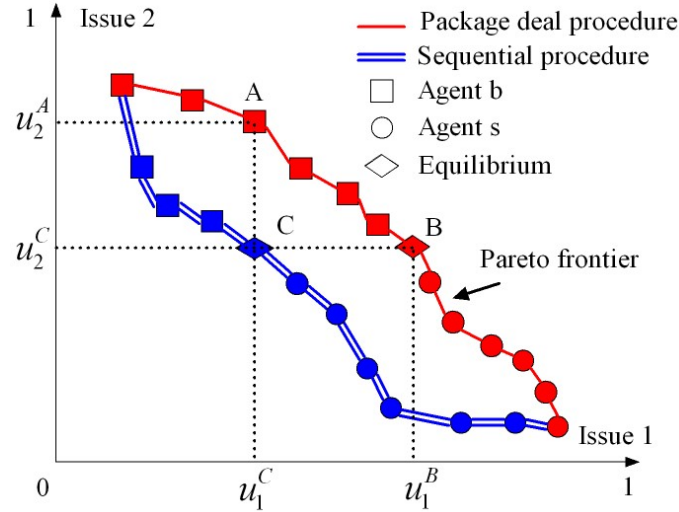


Figure 2.2: An example of Pareto optimal and equilibrium.

strategy unilaterally. Equilibrium ensures the stability of the negotiation. A negotiation procedure may generate one or several equilibrium outcomes. However, not all outcomes are guaranteed to be a Pareto optimal agreement. In multiple issue negotiation, if a change of agreement can improve an agent's benefit on one issue without sacrificing its benefits on other issues, such a change is named the Pareto improvement. An agreement is Pareto optimal when no further Pareto improvements can be made. Therefore, a Pareto optimal agreement is the optimal outcome for multiple issue negotiation. The evaluation results indicate that the *package deal procedure* outperforms the other two procedures by considering the effectiveness to reach Pareto optimality. The *package deal procedure* theoretically ensures that the Pareto optimality can always be reached, but the other two procedures cannot guarantee that. However, the computational cost for Pareto optimality is huge, the *package deal procedure* needs more time to find the Pareto optimality.

In Figure 2.2, an example of Pareto optimality and equilibrium is illustrated. Suppose that Agent  $b$  and Agent  $s$  negotiate on two issues (Issue 1 and Issue 2) with two procedures. The negotiation status by using the *package deal procedure* is indicated by a single-line, and the negotiation status by using the *sequential procedure* is indicated by a double-line. Equilibriums  $B$  and  $C$  are the two agreements achieved by using the two procedures, respectively. Points  $A$  and  $B$  are on the Pareto frontier, and Point  $B$  is the Pareto optimality. Point  $C$  is not the Pareto optimality, because Point  $C$  is dominated by both Point  $A$  ( $u_2^A > u_2^C$ ) and Point  $B$  ( $u_1^B > u_1^C$ ).

In order to overcome the disadvantages of the three common negotiation procedures, a hybrid procedure, named the *coalition deal procedure*, was proposed by Dang and Huhns [DH05] for services negotiation between two interacting agents. The purpose of the *coalition deal procedure* is to make a better trade-off between the *sequential procedure* and the *package deal procedure* to provide an agent with the flexibility to balance time and utility. The basic idea of the *coalition deal procedure* is that all negotiation issues are divided into disjoint partitions. Each partition is negotiated independently by using the *sequential procedure*, and issues inside the same partition are negotiated together by using the *package deal procedure*. The *coalition deal procedure* has the advantages of providing (i) better utility than the *sequential procedure*, (ii) less computational cost than the *package deal procedure*, (iii) more flexible negotiation, and (iv) better management for service negotiation.

### Optimization of Multiple Issue Negotiation

In order to efficiently reach an optimal agreement in multiple issue negotiation, many negotiation strategies, approaches and models have been proposed by researchers.

Fatima et al. [FWJ04a] proposed an agenda-based negotiation to help agents reach the Pareto optimality. Six possible negotiation scenarios were addressed by considering both agents' negotiation deadline and the negotiation strategy, and an optimal negotiation strategy was proposed for each scenario. During the negotiation, through observing an opponent's negotiation behavior, an agent can estimate the state of the current negotiation by comparing with the six possible scenarios, and performs the predefined negotiation strategy in order to optimize the negotiation outcome. However, this approach does not consider the situation that the opponent may change its strategy during the negotiation, which may limit its application in dynamic negotiation environments.

In [FWJ04b], Fatima et al. introduced their studies on a bilateral two-issue (Issues *A* and *B*) negotiation between two self-interested agents. Based on whether a particular issue has or does not have a zone of agreement between the two agents, the two issue negotiation can be divided into four scenarios: (1) both issues have a zone of agreement, (2) only issue *A* has a zone of agreement, (3) only issue *B* has a zone of agreement, and (4) both issues do not have a zone of agreement. During the negotiation, agents can employ either the *sequential procedure* or the *package deal procedure*. The authors proposed an optimal negotiation agenda for

each scenario when agents employ different negotiation procedures. By following the suggested agenda, agents will have more chance to reach an optimal negotiation outcome. However, this approach may have a huge computational cost when the number of negotiated issues becomes large. Agents need to consider all possible situations before the optimal agenda can be found.

In [LLS06], a non-biased mediator is adopted to help agents to achieve Pareto optimality and overcome the difficulty of decisions due to incomplete information and the lack of explicit utility functions. The *package deal procedure* is used in this approach. Firstly, the mediator sends an offer to both agents, and asks each agent to return two equivalent offers. For each agent, the utility gained from the two equivalent offers should be the same as the utility gained from the mediator's offer. By comparing these four equivalent offers from both negotiation participators, the mediator may find a new offer to increase both negotiators' utilities. This process is repeated until the mediator cannot find a further offer to increase both participators' utilities. The final agreement is an approximate value of Pareto optimality. However, such a mediator approach has two shortcomings: (1) in real world negotiation, it will be hard to find a non-biased mediator simultaneously trusted by both agents; and (2) after submitting their offers to the mediator, the agents can do nothing but just wait for the mediator's instructions. If the number of negotiated issues is large, such a wait will be long and the negotiation process will become inefficient. In order to solve the limitations caused by the mediator, in [LSL07], this approach is extended through replacing the mediator's role by negotiation participators. However, when an agent delivers its equivalent offers to its opponent, the agent also takes the risk that its negotiation preference may be leaked to the opponent (if the opponent compares the differences between these equivalent offers). Therefore, this mechanism may not be widely applied in real world negotiations, especially between self-interested agents.

Hindriks and Tykhonov [HT08] proposed a generic framework based on a Bayesian model to learn an opponent's negotiation behavior in multiple issue negotiation. The purpose of this framework is to learn both the opponent's negotiation preference and the utility function. The opponent's preference is estimated based on an assumption that the opponent will make a greater concession on a less-valued issue and a smaller concession on a more-valued issue. Through comparing the opponent's concessions for each issue, the opponent's preference can be estimated. In order to learn the opponent's utility function, three basic functions are proposed. The opponent's utility

function is finally represented as a combination of the three possible functions. By using the estimated preference and utility function, an agent can efficiently search for an optimal negotiation outcome. However, this approach can only generate a satisfying result when the opponents perform a relative simple behavior. If the opponent's behavior becomes complex and changeful, it will not be estimated easily and an optimal negotiation outcome may not be reached effectively.

In [JR04], C. Jonker and V. Robu presented a model for integrative bilateral multiple issue negotiation, in which the *package deal procedure* is adopted. In this model, an opponent may agree to reveal its preference on issues of less-concern, but still keeps its preference private for high-concern issues. A heuristic guessing strategy is proposed to estimate the opponent's preference for those high-concern issues based on existing incomplete preference knowledge and the opponent's historical offers. Finally, complete knowledge of the opponent's preference can be estimated. The estimated preference can be employed by an agent to search for the optimal outcome. However, this model may have a problem in a real world negotiation when an opponent would not like to reveal any information about its preference.

In [FWJ09], Fatima et al. studied bilateral multi-issue negotiation between self-interested agents whose utility functions are nonlinear. The authors argued that even though the *package deal procedure* leads multiple negotiation to Pareto optimality, computing the equilibrium for the *package deal procedure* is not always easy, especially for non-linear utility functions. In order to solve such a problem, the authors introduced two approaches: (1) to approximate non-linear utility functions by linear functions; and (2) to use the *simultaneous procedure* to negotiate issues in parallel but independently. By employing these two approaches, the approximate equilibrium will be found in polynomial time. This paper also showed that although the *package deal procedure* is known to generate Pareto optimal outcomes, the *simultaneous procedure* may outperform in some cases by considering economic properties. However, the first approach may fail to reach an optimal outcome when an approximate linear is hard to find, and the second approach may fail to reach an optimal outcome when the negotiated issues are not absolutely independent.

In this subsection, we reviewed and investigated related work in bilateral multiple issue negotiation. At the beginning, we pointed out that a bi-beneficial agreement may be achieved in multiple issue negotiation, and reviewed three common

negotiation procedures. In order to efficiently achieve optimal negotiation outcomes, several approaches are investigated and discussed. The agenda-based approach [FWJ04a, FWJ04b] predefines the optimal negotiation strategies by considering possible situations during the negotiation. However, when an *environment setting* becomes complex, such as the number of negotiated issues becomes large, or the environment becomes dynamic, the agenda-based approach may become inefficient. The mediator-based approach [LLS06, LSL07] introduces a mediator to help agents search for the optimal outcome. During a negotiation, a mediator will possess complete information on both negotiation participants, and search for an optimal negotiation outcome for them. However, in a real life situation, such a non-biased mediator, who is trusted by both negotiation participants, may not be hard to find. Learning approaches [HT08, JR04] are also employed in multiple issue negotiation to predict opponent's preferences. However, these approaches may face the same problem when necessary prior knowledge cannot be acquired. Because the Pareto optimality is not easily achieved in a non-linear situation, an approximate optimal outcome [FWJ09] is proposed to increase the computational efficiency. However, approximate optimality is still not the best solution. In order to solve these problems, an opponent's preference prediction approach and an optimization approach for multiple issue negotiation will be proposed in Chapter 4 of this thesis to efficiently and effectively search for optimal negotiation outcomes.

## 2.3 Multilateral Level

In this section, techniques and approaches for multilateral negotiations are reviewed. Subsection 2.3.1 investigates and discusses main related work on negotiation partner selection, and Subsection 2.3.2 reviews the main related work for multilateral negotiation.

### 2.3.1 Negotiation Partner Selection

In multilateral negotiation, an agent may negotiate with many opponents. However, not all opponents have the potential to reach an agreement with the agent. For example, some opponents may suddenly leave off a negotiation midway; some opponents have lower qualifications than the agent's requirement; and some opponents do not have an agreement zone with the agent. Therefore, it is not necessary

for the agent to perform a sophisticated negotiation with all opponents. In this Subsection, we investigate and discuss the main related work for filtering out unqualified opponents before a multilateral negotiation starts.

Social network analysis has been used for a long time by sociologists as a mechanism to infer and explain social behaviors. In [SS01], J. Sabater and C. Sierra used techniques in social network analysis in a reputation system to solve partner selection problems in multilateral negotiation. They proposed a reputation model to monitor how an existing contract is fulfilled by an opponent. If the fulfillment of the contract from an opponent is worse than that promised, then the opponent will be assigned a low score on its reputation. If the fulfillment of the contract of an opponent is better than expected, opponent will have a high score on its reputation. Once an agent needs to select partners for a future negotiation, the reputation scores for each potential opponent will be employed as references to decide whether an opponent will be selected. The shortcoming of this approach is that if an agent never had an interaction with an opponent before, then the agent would lack historical records as a reference to judge the opponent's fulfillment ability, and to perform an efficient selection.

The trust-based approach is also one of the most popular mechanisms for partner selection. In [RJSG04], Ramchurn et al. proposed a trust-based model to consider both *confidence* and *reputation* in evaluating a negotiation partner. The *confidence* is an agent's personal view on a negotiation partner, which is generated by the agent itself based on evidence from past direct interactions with the partner. The *reputation* is a social view of a negotiation partner, which indicates the perception of groups of agents on the negotiation partner's ability. Usually, the *reputation* can be acquired from other trusted agents. When a potential partner needs to be evaluated, both *confidence* and *reputation* of the partner are combined as a *trust*. The value of *trust* can be used to determine which partners are selected for a negotiation. By comparison with Sabater's approach [SS01], this approach takes both individual and social opinions into account when an opponent is evaluated. However, it still has a limitation in handling the evaluation on a new opponent.

As shown in [SS01, RJSG04], when an agent needs to decide whether an opponent can be selected, the agent's past experience with the opponent or the opponent's reputation provided by a third-party agent is usually considered. However, Fullam and Barber [FB07] argued that not all information for trust computation is accurate and reliable, and may be influenced by parameters such as: frequency of transactions

with the opponent, trustworthiness of the opponent, and accuracy of the provided reputations. To address such a problem, the authors proposed a Markov Decision Process (MDP) for dynamically learning the best source of trust information. In MDP, both an experience resource and a reputation resource are considered, and a learning process is introduced to dynamically balance between these two information resources. Opponents which are believed to have a potential ability to fulfill an agent's requirement will be finally selected.

Brzostowski and Kowalczyk [BK05, BK04] proposed a possibilistic model based on Case-Based Reasoning (CBR) theory [Lea96, GS95] to solve the partner selection problem. Firstly, negotiations in the historical records are summarized by considering a *situation attribute* and an *outcome attribute*. The *situation attribute* indicates an opponent's negotiation behavior in the historical records, and the *outcome attribute* indicates the historical outcome by negotiating with the opponent. Based on an assumption that "the more similar the situation description attributes are, the more likely that the outcome attributes are similar", the possibility that a successful negotiation may be performed with each potential opponent is estimated. Through comparing an opponent's *situation attribute* with the historical records, the opponent's situation can be approximated by existing cases. Then the potential outcome through negotiating with the opponent can be estimated. Finally, all potential opponent are ranked according to the expected outcome. In [BK07], this work was extended by employing a Fuzzy Logic function [YRP94, KY95]. A fuzzyfication is used in the case matching process to improve the efficiency of this model. However, such a case-based approach may have a shortcoming when applied in a dynamic environment, ie. because an opponent may modify its behavior during a negotiation, a similar *situation attribute* may not result in a similar *outcome attribute*.

Munroe et al. [MLd04, ML05] proposed a motivation-based partner selection mechanism to evaluate identified opponents. Opponents are evaluated in terms of the amount of conflict they are expected to bring to a negotiation, and the amount of cost they are expected to spend in the negotiation. To perform the selection process, firstly, an agent sends its negotiation goal, negotiable attributes, and an opponent's historical information to an *issue analyser*. The *issue analyser* calculates a possible conflict between the agent and the opponent. Then information about current negotiation resources, the agent's reservation, and the opponent's price profile are sent to a *resource manager*. The *resource manager* calculates the expected cost of the opponent. Then, both the possible conflict and expected cost

are sent to an *opponent rater* to rank the opponent. Finally, opponents are selected based on the ranking results. The advantage of this approach is to consider both potential conflicts and costs, but the selection process is not sensitive to a dynamic environment, such as an e-marketplace.

Banerjee and Sen [BS00] proposed a multinomial distribution-based mechanism for partner selection. The purpose of this mechanism is to select an opponent who is most likely to return a maximum total utility. Firstly, for each potential opponent, a payoff-structure is constructed, which indicates all possible utilities that an agent may gain by negotiating with the opponent. Then pairwise comparisons among all opponents' payoff-structures are performed. Finally, the opponent who has the greatest probability of offering the maximum utility to the agent will be selected. However, for an unknown opponent, the payoff-structure is usually not available, and the selection result may not be effective.

In this subsection, some related work for partner selection was reviewed and discussed. Different criteria were considered to evaluate a potential opponent. In detail, the approaches introduced in [SS01, RJSG04, FB07] focus on an opponent's reputation, the approach introduced in [BK05, BK04] is based on the dependency between an opponent's negotiation setting and the negotiation outcome, the approaches in [MLd04, ML05] consider both negotiation conflicts and costs, and the approach in [BS00] considers the expected utility. However, all of these approaches consider only an agent's own benefit when a partner is evaluated, but not the benefits of all negotiation participators. In Chapter 5, a dual-concern-based partner selection approach is proposed to overcome this limitation by the consideration and balance of both an agent's and the opponents' benefits during the process of partner selection.

### 2.3.2 Multilateral Negotiation

In this subsection, the main related work on the negotiation strategies, protocols and models in multilateral negotiation are investigated and discussed. Both a static negotiation environment and a dynamic negotiation environment are considered.

#### Static Environment

In [NJ03, NJ04a, NJ04b], Nguyen and Jennings proposed a flexible model about commitments in multilateral negotiations. In order to maximize an agent's utility in



multilateral negotiation, a *coordinator* and a *commitment manager* are introduced. Each *bilateral negotiation* is represented as a single *thread*. During the negotiation, the *coordinator* decides the negotiation strategies for each *thread*. After each round, each *thread* reports its negotiation status to the *coordinator*. If any *thread* reaches an agreement with a particular opponent, this *thread* will be terminated and waits for the negotiation deadline. Then the *coordinator* notices other *threads* about the new reservation for the negotiation, and may modify negotiation strategies for these *threads*. The *commitment manager* handles commitment and decommitment issues. For instance, the *commitment manager* needs to decide whether a proposed offer from a *thread* should be accepted based on the agent's current commitment and its decommitment strategy. If a new offer can increase the agent's utility after a decommitment fee, then the *commitment manager* will renege from an existing committed deal. Otherwise, the existing committed deal will not be replaced. The result of the *commitment manager* on each new offer will be passed through the *coordinator* for cross checking with other *threads* before getting back to the calling *thread*. By following such a process, the agent can maximize its utility in a multilateral negotiation. However, this model may not work properly in a dynamic environment, because an opponent who makes a contract with the agent may also decommit the contract, and this model does not take this situation into account.

Hemaissia et al. [HSLM06, HSLM07] introduced a multilateral multi-issue negotiation protocol for a cooperative context. In order to take into account the complexity that exists between the negotiated issues, a multi-criteria decision aiding (MCDA) tool named MYRIAD [LH05] is employed. At the beginning of a negotiation, a *mediator* makes a proposal and broadcasts the proposal to all agents. Once an agent receives the proposal, the agent will make a decision based on its situation. If the agent has no chance to gain more benefit than the proposal in the remainder of the negotiation, then the agent has to accept the proposal. Otherwise, the agent will reject the proposal and return a counter-proposal to the *mediator*. Then the *mediator* will make a new proposal by considering all counter-proposals from unsatisfied agents. This process will be repeated until a proposal is accepted by all agents or no more proposal can be made by the *mediator*, in which case all agents must accept a predefined default proposal. However, by employing such a protocol, even though an all-acceptable agreement can be reached among negotiators, such an agreement may not be the optimal outcome.

In [End06], Endriss analyzed several key issues in bilateral negotiation and proposed a monotonic concession protocol for multilateral negotiation. This protocol contains three major steps: (1) all agents make their initial proposal at the first round of a negotiation; (2) in each negotiation round, each agent either makes a concession or sticks with its current proposal; and (3) Step (2) is repeated until either a conflict situation arises (no agent makes a concession) or an agreement is reached. In addition, in order to help agents to efficiently reach an all accepted agreement, seven concession strategies for different negotiation strategies are proposed. Each concession strategy has both advantages and disadvantages. However only *strong concession*, *weak concession* and *Pareto concession* are proven to be verifiable in a multilateral negotiation. Finally, five common negotiation strategies are introduced to help agents to efficiently reach an agreement. However, this protocol cannot handle an upcoming outside option in a dynamic negotiation environment.

### Dynamic Environment

In this subsection, negotiation models for dynamic environments are investigated and discussed.

Sim et al. [Sim02, SC03] introduced a market-driven model to help agents to make adjustable rates of concession by reacting to changing market situations. To determine the amount of concession for each negotiation round in a multilateral environment, four mathematical functions are proposed to guide agents in making decisions, which are *trading opportunity function*, *trading competition function*, *trading time function*, and *eagerness function*. The *trading opportunity function* monitors the probability that an agent's proposal can be accepted by at least one of its negotiation opponents. Usually, the higher the probability, the more chance that the agent can get the expected utility, and the less concession the agent would like to make during the negotiation. The *trading competition function* monitors the situation of competition in a marketplace. Usually, an agent will make a large concession when the competition is high, and a small concession when the competition is low. The *trading time function* calculates an agent's concession based on time consideration. Negotiation tactics, such as *Boulware*, *Concedure* and *Linear*, are employed in this function. Finally, the *eagerness function* monitors an agent's eagerness to achieve an agreement for the current negotiation. A higher *eagerness* will lead to a greater concession during the negotiation, while a lower *eagerness* will

lead to a smaller concession. By employing these four functions, an agent can make reasonable concession in a multilateral negotiation in order to maximize its utility, and also efficiently reach agreement.

In [OR01], Oliveira and Rocha proposed an e-market architecture model to handle agent negotiation in dynamic e-marketplaces. In this model, each participator of an e-market is served by two software agents, ie. a *market agent* and a *organization agent*. The *market agent* focuses on the pre-processing of a negotiation, and the *organization agent* controls the negotiation process. Once an e-market participator submits its requirement for a particular item to the system, the *market agent* will represent the requirement as several sub-goals. Meanwhile, the *market agent* will send a set of invitations (one for every sub-goal) to the system, and perform a partner selection process to filter out unfavorable opponents before a negotiation starts. Once the negotiation partners are confirmed, the *organization agent* will perform a negotiation between these partners by considering both the individual and e-market's situations. During the negotiation, the *organization agent* will dynamically update information about the e-market, and may modify its negotiation behaviors when necessary. Finally, when an agreement is achieved, the *organization agent* will execute the contract that it committed to.

Li et al. [LSG05, LGS06] proposed a *synchronized multi-threaded process* and a *dynamic multi-threaded process* to handle the multilateral negotiation in both static and dynamic negotiation environments, respectively. Each bilateral negotiation between an agent and an opponent is considered as a *single-threaded process*. For the *synchronized multi-threaded process* without considering future possible upcoming outside options, the expected utility for each *single-threaded process* is estimated in each negotiation round by four heuristic approaches, which are *conservative estimation*, *medium estimation*, *uniform approximation*, and *learning*. Then in order to maximize self's utility, the agent will adjust its attentions among opponents based on the estimation of expected utilities. For the *dynamic multi-thread process* considering future possible upcoming outside options, a *Poisson process* is proposed to predict the number of upcoming outside options in the next round or few negotiation rounds. Then, by employing the historical records of each *single-threaded process* and the estimation approaches in the *synchronized multi-threaded process*, the utility that the agent expected from the *dynamic multi-threaded process* is predicted. The agent can use this predicted result to adjust its negotiation strategies and reservation offers for each *single-threaded process* within a *dynamic multi-thread*

*process.*

In this subsection, we investigated and discussed strategies, approaches and models for multilateral negotiations. The approaches introduced in [NJ03, NJ04a, NJ04b, HSLM06, HSLM07, End06] focus on a static environment. The limitation of these approaches is that future possible outside options are not considered. Therefore, once a multilateral negotiation starts, the outside options cannot join the negotiation anymore. However, by considering real-life negotiations, such as negotiation in e-marketplaces, the future possible upcoming outside options should be considered. Although the approaches introduced in [Sim02, SC03, OR01, LSG05, LGS06] can handle negotiations in a dynamic environment, they can still be improved in two aspects: (1) to predict the future possible changes of a dynamic environment actively, but not just monitor the changes of the environment passively; and (2) to consider multiple preferences when agents negotiate with different opponents. In order to solve these two problems, a market-driven based approach is proposed in Chapter 6 to deal with single issue negotiation in dynamic multilateral environments, and a market-based approach is proposed in Chapter 7 to handle multiple issue negotiation in dynamic multilateral environments.

## 2.4 Multi-Negotiation Level

The *Multi-Negotiation Level* represents a situation in which an agent needs to perform several negotiations in order to reach a global goal, and relationships between these negotiations are somehow related. At the present time, not very much work has been done on this level. In this section, some related work on multiple related negotiations is reviewed and discussed.

### 2.4.1 Multiple Related Negotiation

Zhang et al. proposed a meta-level coordination approach to solve a negotiation chain problem in a semi-cooperative multi-agent system [ZL02, ZLA05, ZL07]. In a complex negotiation chain scenario, agents need to concurrently perform several negotiations in order to complete their goals on time. The order and structure in which negotiations occur may impact on the performance of both individual agents and the whole system. A pre-negotiation approach is introduced to transfer meta-level information, such as starting time, deadlines and durations of negotiation to

decision factors. By using these factors, agents can estimate the success rate for each concurrent negotiation, and model the flexibility for the negotiation. For example, when a *consumer agent* wants to purchase a computer and some computer hardware, the *consumer agent* negotiates with a *computer producer agent* on issues related to the computer and a *hardware producer agent* on issues related to the hardware at the same time. The *computer producer agent* needs to arrange procedures of *get hardware*, *get software*, *install software*, and *shipping computer* according to the time series. The *hardware producer agent* needs to handle requests from both the *consumer agent* and *computer producer agent* at the same time. The outcome of these complex negotiations is a well organized time series that can ensure both the computer and the hardware can be delivered to the *consumer agent* on time. However, the shortcoming of this approach is that only the time information is considered to arrange related negotiations, without specification of how to maximize the global utility considering all related negotiations.

He et al. [HRLJ06] proposed an approach to solve the optimization problem in Supply Chain Management (SCM). In order to handle procedures of components order, computer assembly, customer order and customer delivery for a *computer manufacturer*, a *component agent*, a *factory agent* and a *customer agent* are proposed. Each agent works in a specified procedure to maximize local payoffs. Meanwhile, agents cooperate to maximize the global outcome. A market predictor and a price tracker are employed by a *component agent* to estimate market situations for a *computer component*. Fuzzy rules are employed by a *customer agent* to heuristically calculate offer prices for customers. Also a production scheduling strategy is employed by a *factor agent* to allocate supply resources and factory time. However, this approach only solves the optimization problem for cooperative negotiations, and does not handle competitive situations.

Proper and Tadepalli [PT09] proposed an assignment-based decomposition approach by employing the Markov Decision Process (MDP) to solve an optimal decision making problem in an assignment decomposition between multiple collaborative agents. A centralized controller which has relevant information about the states of all agents is assumed in their approach. The approach contains two levels, where the upper level focuses on task assignment, and the lower level focuses on task execution. The centralized controller solves the assignment problem through a search algorithm and solves the task execution problem through coordinated reinforcement learning. After the controller solves problems in these two levels, solutions will

be sent to agents for implementation. However, this approach still only considers a cooperative environment, and fails to handle related negotiations in competitive environments.

In summary, the approaches introduced in [ZL02, ZLA05, ZL07] employed a meta-level coordination approach to solve negotiation chain problems by considering time series, but not attempting to maximize the global utility. The approaches in [HRLJ06, PT09] introduced optimization approaches for multiple related negotiations, but only a cooperative situation is considered, and may not handle a competitive environment. In order to solve these problems, a Multi-Negotiation Network (MNN) and a Multi-Negotiation Influence Diagram (MNID) are proposed in Chapter 8 to optimize the outcome of multiple related negotiations. The proposed approach can be used in both cooperative and competitive negotiations.

## 2.5 Summary

Agents usually need to modify their negotiation strategies, approaches and protocols when a negotiation environment changes. At the beginning of the chapter, we indicated how different complexity levels of negotiation environments affect agent negotiation behaviors. Some related work in each level is investigated and discussed in detail, which include *agent behavior prediction* (Subsection 2.2.1), *optimization of multiple issue negotiation* (Subsection 2.2.2), *negotiation partner selection* (Subsection 2.3.1), *multilateral negotiation* (Subsection 2.3.2), and *multiple related negotiation* (Subsection 2.4.1).

Even though many researchers have proposed different negotiation protocols, negotiation procedures, negotiation strategies, and negotiation models to solve these research issues in different levels, limitations still exist which require further research and improvement. This thesis proposes several new approaches to solve some limitations of current approaches in each negotiation level. Firstly, a regression-based partner behavior prediction approach is proposed to efficiently estimate an opponent's negotiation behaviors in bilateral negotiation (Chapter 3). Secondly, an algebraic algorithm and a geometric algorithm are proposed to search for mutually beneficial agreement in bilateral multiple issue negotiation (Chapter 4). Thirdly, linear and non-linear partner selection approaches are proposed to filter out unqualified partners before negotiations are performed between multilateral parties (Chapter 5). Fourthly, a market-driven negotiation approach is proposed to handle single issue

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negotiations in a dynamic multilateral environment (Chapter 6). Fifthly, a market-based negotiation approach is proposed to handle multiple issue negotiations in a dynamic multilateral environment (Chapter 7). Lastly, a Multi-Negotiation Network and a Multi-Negotiation Influence Diagram are proposed to handle multiple related negotiations, and to optimize the outcome of these related negotiations (Chapter 8).

The following chapters will concentrate on solving each individual problem, and on overcoming the limitations of previous work.

# Chapter 3

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## Agent Behavior Prediction in Bilateral Single Issue Negotiation

Chapters 3 and 4 focus of research issues on the bilateral negotiation, (the first level of our proposed hierarchical negotiation view).

### 3.1 Introduction

In this chapter, an agent behavior prediction approach in bilateral single issue negotiation is introduced. As described in Subsection 2.2.1, in most situations, agents do not have complete information about their opponents, which may cause difficulties to make a decision on future negotiation, such as how to select suitable partners for further negotiation [BK04, MLd04] or how to generate a suitable counter-offer for the next negotiation round [PSJ98]. Estimation approaches which can predict uncertain situations and possible changes in future are required for helping agents to perform efficient negotiation by considering uncertainties. Research on such an issue has been an active area in recent years. Many estimation approaches have been proposed [ZS98, CN04, CKO01, RZ07b, RZ07a] to handle the opponent behavior estimation problem. However, these estimation approaches still have some limitations in terms of the efficiency and effect of the estimation results.

Bayesian learning [ZS98, ZS97, NJ05, NJ06, BK06] is one of the most popular approaches to estimate an opponent's behavior. The Bayesian-learning-based [BK07] approaches usually contain two steps. Firstly, based on the prior domain knowledge about a negotiation and hypotheses on the possible negotiation outcomes, a Bayesian learning algorithm can be generated to represent the likelihood for each hypothesis. Secondly, during a negotiation, the likelihood for each hypothesis is dynamically updated according to an opponent's negotiation behaviors, and an agent



can find the most possible negotiation outcome based on its hypotheses. However, when the domain knowledge is not available, and/or an agent cannot generate reasonable hypotheses for possible negotiation outcomes, the performance of the Bayesian-learning-based approaches will be limited.

Machine learning [GP06] is another kind of popular mechanism adopted by researchers in agent behavior estimation. In general, this kind of approach contains two steps in order to properly estimate an opponent's behavior. In the first step, the proposed estimation function is required to be well trained by training data. Therefore, the performance of the estimation function is somehow decided by the training result. The training data could be both synthetic or collected from the real world. Usually, synthetic data are helpful in training a function to enhance its problem solving skill for some particular issues, while real world data can help the function to improve its ability in complex problem solving. After the estimation function is trained, the function is employed to predict an opponent's behavior in the second step. However, no matter how many data are employed to train the estimation function, the training data may still not be comprehensive enough to cover all situations in reality. Therefore, it is very likely that the behavior estimation results cannot truly reflect an opponent's behavior which is not included in the training data. Also, when the negotiation environment becomes open and dynamic, agents with different negotiation purposes, preferences and strategies can enter and leave a negotiation process dynamically. The machine learning based agent behavior estimation approaches may not work well in such an uncertain situation by considering the limitations of (1) lack of sufficient data to train the system and (2) requesting plenty of resources in each training process.

In order to address those issues mentioned above, in this chapter we propose three regression functions to analyze and estimate an opponent's behaviors in negotiation, which are linear, power and quadratic regression functions. By comparison with Bayesian learning and machine learning mechanisms, the proposed approach only uses the historical offers in the current negotiation to estimate an opponent's behaviors without requiring any additional training process or domain knowledge, so it is suitable to be used in an open and dynamic negotiation environment. Also, because the proposed approach does not make any strict assumption on an agent's negotiation strategy, it can be employed widely in negotiation by different types of agents. Furthermore, the proposed approach not only estimates an opponent's possible behaviors in the future, but also provides the likelihood for each predicted

behavior.

The rest of this chapter is organized as follows: Section 3.2 introduces some general agent behaviors in negotiation. Section 3.3 introduces the three proposed regression functions, respectively. Section 3.4 introduces the approach to predict an opponent's behaviors by employing the regression functions. Section 3.5 illustrates the performance of the proposed regression functions through experiments. Section 3.6 summarizes this chapter.

## 3.2 An Agent's Behavior in Negotiation

In this section, we introduce some general agent behaviors in single-issue bilateral negotiations. Generally, there are four kinds of behaviors which agents usually perform in a negotiation. The four possible behaviors are *Boulware*, *Linear*, *Conceder* and *Sit-and-Wait* [FWJ04a, Sim05].

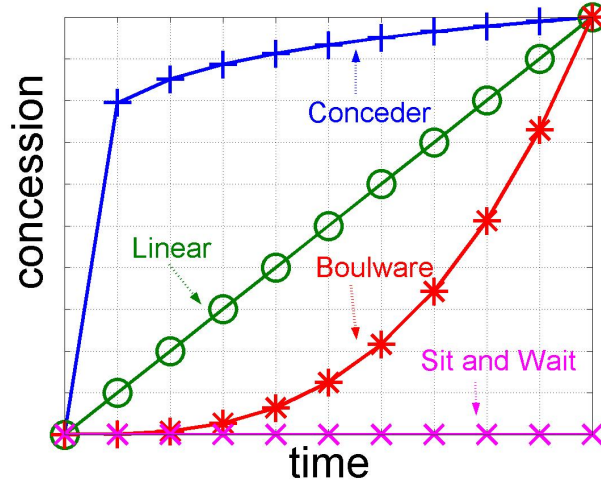


Figure 3.1: Agents' behaviors in negotiation

In Figure 3.1, we illustrate the four possible agent behaviors. Let the  $x$ -axis stand for the negotiation rounds and the  $y$ -axis stand for the concession that an agent can make in negotiation. Details of the four possible behaviors are as follows:

- **Boulware:** the rate of change in the slope is increasing, corresponding to small concessions in the early rounds but large concessions in the later rounds.
- **Linear:** the rate of change in the slope is zero, corresponding to making a constant concession throughout whole negotiation.

- Conceder: the rate of change in the slope is decreasing, corresponding to large concessions in the early rounds but small concession in the later rounds.
- Sit-and-Wait: the rate of change of the value of slope and the slope itself are always zero, corresponding to not making any concession throughout a negotiation.

Since the curves of an agent's possible behaviors illustrated in Figure 3.1 are monotonic, so we introduce three regression functions to predict an opponent's behavior in the single-issue bilateral negotiation for different accuracy purposes.

### 3.3 Regression Analysis in Agent Negotiation

#### 3.3.1 Linear Regression Function

Firstly, we propose the linear regression function as follows:

$$R(t) = b \times t + a \quad (3.1)$$

where  $t$  ( $0 \leq t \leq \tau$ ) denotes the negotiation time and  $a, b$  are the coefficients which need to be calculated. Both coefficients  $a$  and  $b$  are independent of  $t$ .

Let pairs  $(t_0, \hat{u}_0), \dots, (t_n, \hat{u}_n)$  be the historical offers from an opponent in a negotiation, where  $t_i$  ( $t_i < t_{i+1}$ ) indicates the negotiation round and  $\hat{u}_i$  ( $\hat{u}_i \leq \hat{u}_{i+1}$ ) indicates the utility that an agent gained from the opponent. Let  $\varepsilon_i$  be the difference between the estimated results ( $u_i, u_i = R(t_i)$ ) and the real utility ( $\hat{u}_i$ ) at round  $t_i$ . It is assumed that all  $\varepsilon_i$  obey the Normal distribution, then each historical offer can be represented as  $\hat{u}_i = b \times t_i + a + \varepsilon_i$ , and the joint probability density function for  $\hat{u}_i$  is defined as follows:

$$\begin{aligned} L &= \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2\sigma^2}(\hat{u}_i - bt_i - a)^2\right] \\ &= \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^n (\hat{u}_i - bt_i - a)^2\right] \end{aligned} \quad (3.2)$$

In order to minimize the error between the predicted results and real utilities (ie. maximize  $L$ ), obviously  $\sum_{i=1}^n (\hat{u}_i - bt_i - a)^2$  should achieve its minimum value. Let

$$Q(a, b) = \sum_{i=1}^n (\hat{u}_i - bt_i - a)^2 \quad (3.3)$$

We calculate the first-order partial derivative for  $Q(a, b)$  on  $a$  and  $b$  respectively, and let the results equal to zero as follows:

$$\begin{cases} \frac{\partial Q}{\partial a} = -2 \sum_{i=1}^n (\hat{u}_i - bt_i - a) = 0 \\ \frac{\partial Q}{\partial b} = -2 \sum_{i=1}^n (\hat{u}_i - bt_i - a)t_i = 0 \end{cases} \quad (3.4)$$

Then it equals:

$$\begin{cases} na + (\sum_{i=1}^n t_i)b = \sum_{i=1}^n \hat{u}_i, \\ (\sum_{i=1}^n t_i)a + (\sum_{i=1}^n t_i^2)b = \sum_{i=1}^n t_i \hat{u}_i \end{cases} \quad (3.5)$$

Because the value of Equation 3.5's coefficient matrix is:

$$\begin{aligned} \begin{vmatrix} n & \sum_{i=1}^n t_i \\ \sum_{i=1}^n t_i & \sum_{i=1}^n t_i^2 \end{vmatrix} &= n \sum_{i=1}^n t_i^2 - (\sum_{i=1}^n t_i)^2 \\ &= n \sum_{i=1}^n (t_i - \bar{t})^2 \neq 0 \end{aligned} \quad (3.6)$$

So both coefficients  $a$  and  $b$  have an unique solution, which is:

$$\begin{cases} a = \frac{\sum_{i=1}^n \hat{u}_i \sum_{i=1}^n t_i^2 - \sum_{i=1}^n t_i \sum_{i=1}^n t_i \hat{u}_i}{n \sum_{i=1}^n t_i^2 - (\sum_{i=1}^n t_i)^2} \\ b = \frac{n \sum_{i=1}^n t_i \hat{u}_i - \sum_{i=1}^n t_i \sum_{i=1}^n \hat{u}_i}{n \sum_{i=1}^n t_i^2 - (\sum_{i=1}^n t_i)^2} \end{cases} \quad (3.7)$$

Then by employing the coefficients  $a$  and  $b$ , a linear regression function can be generated. The advantage of the linear regression function is that it is easily implemented. However the disadvantage of the linear regression is that it can only represent the opponent's behaviors, which belong to *Linear* and *Sit-and-Wait* as follows:

- Linear: when  $b \neq 0$ , the rate of change in the slope is zero, corresponding to a constant concession throughout a negotiation.
- Sit-and-Wait: When  $b = 0$ , the rate of change of the slope and the value of slope itself are always zero, corresponding to not making any concession throughout a negotiation.

### 3.3.2 Power Regression Function

In order to represent all possible opponent's behaviors, we propose a power regression function as follows:

$$R(t) = a \times t^b \quad (3.8)$$

Firstly, we perform the equivalence transformation on Equation 3.8:

$$\ln(R(t)) = \ln(a \times t^b) = \ln(a) + b \times \ln(t) \quad (3.9)$$

Let  $u^* = \ln(R(t))$ ,  $a^* = \ln(a)$  and  $t^* = \ln(t)$ , Equation 3.9 can be rewritten as  $u^* = a^* + b \times t^*$ . Then by employing the approach introduced in the Subsection 3.3.1 (see Equations 3.2 to 3.5), we can obtain solutions for coefficients  $a$  and  $b$  as follows:

$$\begin{cases} a = \exp\left(\frac{\sum_{i=1}^n \hat{u}_i^* \sum_{i=1}^n t_i^{*2} - \sum_{i=1}^n t_i^* \sum_{i=1}^n t_i^* u_i^*}{n \sum_{i=1}^n t_i^{*2} - (\sum_{i=1}^n t_i^*)^2}\right) \\ b = \frac{n \sum_{i=1}^n t_i^* \hat{u}_i^* - \sum_{i=1}^n t_i^* \sum_{i=1}^n u_i^*}{n \sum_{i=1}^n t_i^{*2} - (\sum_{i=1}^n t_i^*)^2} \end{cases} \quad (3.10)$$

Compared with the linear regression function, the power regression function can represent all four common behaviors of an opponent as follows:

- Boulware: when  $b > 1$ , the rate of change in the slope is decreasing, corresponding to small concessions in the early rounds but large concessions in later rounds.
- Linear: when  $b = 1$ , the rate of change in the slope is zero, corresponding to a constant concession throughout a negotiation.
- Conceder: when  $0 < b < 1$ , the rate of change in the slope is increasing, corresponding to large concessions in the early rounds but small concessions in the later rounds.
- When  $b = 0$ , the rate of change of the slope and the value of slope itself are always zero, corresponding to not making any concession throughout a negotiation.

### 3.3.3 Quadratic Regression Function

Using a quadratic regression function is another option to represent an opponent's possible behaviors. The quadratic regression function is proposed as follows:

$$R(t) = a \times t^2 + b \times t + c \quad (3.11)$$

Let  $x = t^2$  and  $y = t$ , then Equation 3.11 is firstly transferred to a linear function as follows:

$$R(t) = a \times x + b \times y + c \quad (3.12)$$

The joint probability density function for the difference between the predicted value  $u_i$  and the real value  $\hat{u}_i$  is:

$$\begin{aligned} L &= \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2\sigma^2}(\hat{u}_i - ax_i - by_i - c)^2\right] \\ &= \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^n (\hat{u}_i - ax_i - by_i - c)^2\right] \end{aligned} \quad (3.13)$$

In order to minimize the prediction error (maximize  $L$  in math),  $\sum_{i=1}^n (\hat{u}_i - ax_i - by_i - c)^2$  should achieve its minimum value. Let

$$Q(a, b, c) = \sum_{i=1}^n (\hat{u}_i - ax_i - by_i - c)^2 \quad (3.14)$$

We calculate the first-order partial derivative for  $Q(a, b, c)$  on  $a$ ,  $b$  and  $c$ , and let the results equal to zero.

$$\begin{cases} \frac{\partial Q}{\partial a} = -2 \sum_{i=1}^n (\hat{u}_i - ax_i - by_i - c)x_i = 0 \\ \frac{\partial Q}{\partial b} = -2 \sum_{i=1}^n (\hat{u}_i - ax_i - by_i - c)y_i = 0 \\ \frac{\partial Q}{\partial c} = -2 \sum_{i=1}^n (\hat{u}_i - ax_i - by_i - c) = 0 \end{cases} \quad (3.15)$$

Equation 3.15 can be rewritten as follows:

$$\begin{cases} (\sum_{i=1}^n x_i^2)a + (\sum_{i=1}^n x_i y_i)b + (\sum_{i=1}^n x_i)c = \sum_{i=1}^n x_i \hat{u}_i \\ (\sum_{i=1}^n x_i y_i)a + (\sum_{i=1}^n y_i^2)b + (\sum_{i=1}^n y_i)c = \sum_{i=1}^n y_i \hat{u}_i \\ (\sum_{i=1}^n x_i)a + (\sum_{i=1}^n y_i)b + nc = \sum_{i=1}^n \hat{u}_i \end{cases} \quad (3.16)$$

Then let

$$PU = \begin{vmatrix} \sum_{i=1}^n x_i^2 & \sum_{i=1}^n x_i y_i & \sum_{i=1}^n x_i \\ \sum_{i=1}^n x_i y_i & \sum_{i=1}^n y_i^2 & \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_i & \sum_{i=1}^n y_i & n \end{vmatrix} \quad (3.17)$$

$$PA = \begin{vmatrix} \sum_{i=1}^n x_i \hat{u}_i & \sum_{i=1}^n x_i y_i & \sum_{i=1}^n x_i \\ \sum_{i=1}^n y_i \hat{u}_i & \sum_{i=1}^n y_i^2 & \sum_{i=1}^n y_i \\ \sum_{i=1}^n \hat{u}_i & \sum_{i=1}^n y_i & n \end{vmatrix} \quad (3.18)$$

$$PB = \begin{vmatrix} \sum_{i=1}^n x_i^2 & \sum_{i=1}^n x_i \hat{u}_i & \sum_{i=1}^n x_i \\ \sum_{i=1}^n x_i y_i & \sum_{i=1}^n y_i \hat{u}_i & \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_i & \sum_{i=1}^n \hat{u}_i & n \end{vmatrix} \quad (3.19)$$

$$PC = \begin{vmatrix} \sum_{i=1}^n x_i^2 & \sum_{i=1}^n x_i y_i & \sum_{i=1}^n x_i \hat{u}_i \\ \sum_{i=1}^n x_i y_i & \sum_{i=1}^n y_i^2 & \sum_{i=1}^n y_i \hat{u}_i \\ \sum_{i=1}^n x_i & \sum_{i=1}^n y_i & \sum_{i=1}^n \hat{u}_i \end{vmatrix} \quad (3.20)$$

Because  $PU \neq 0$ , so coefficients  $a$ ,  $b$  and  $c$  have a unique solution as follows:

$$\begin{cases} a = \frac{PA}{PU} \\ b = \frac{PB}{PU} \\ c = \frac{PC}{PU} \end{cases} \quad (3.21)$$

The quadratic regression function can also represent the four common behaviors of agents as follows:

- Boulware: when  $a > 0$ , the rate of change in the slope is decreasing, corresponding to small concessions in the early rounds but large concessions in later rounds.
- Linear: when  $a = 0$  and  $b \neq 0$ , the rate of change in the slope is zero, corresponding to a constant concession throughout a negotiation.
- Conceder: when  $a < 0$ , the rate of change in the slope is increasing, corresponding to large concessions in the early rounds but small concessions in the later rounds.
- When  $a = b = 0$  and  $c \neq 0$ , the rate of change of the slope and the value of slope itself are always zero, corresponding to not making any concession throughout a negotiation.

### 3.4 Opponent Behaviors Prediction

In the previous section, we proposed three regression functions to predict an opponent's behaviors. However, it has to be mentioned that the proposed regression functions can only provide an estimation on an opponent's possible behaviors, which might not exactly accord with the opponent's real behaviors. In this chapter, we make an assumption that the differences ( $\varepsilon$ ) between the estimation behaviors and

the real behaviors obey the Gaussian distribution  $N(0, \sigma^2)$  [PR96]. The reason for such an assumption is that most estimated utilities from the opponent are close to the real utilities. Thus, if the deviation  $\sigma^2$  can be calculated, we can make a precise decision on the range of an opponent's behaviors. It is known that there is more than 99% probability that the opponent's real utilities will be located in the interval  $[u - 3\sigma, u + 3\sigma]$ . In this section, we introduce an approach to calculate the deviation  $\sigma$  and the interval to accurately represent an opponent's utility.

To calculate the deviation  $\sigma$ , we firstly calculate the distance between the estimated utility  $u_i$  ( $u_i = R(t)$ , for  $t = i$ ) and an opponent's real utility as follows:

$$d_i = \hat{u}_i - u_i \quad (3.22)$$

It is known that all  $d_i$  ( $i \in [1, n]$ ) obey the Gaussian distribution  $N(0, \sigma^2)$ . Then  $\sigma$  can be calculated as follows:

$$\sigma = \sqrt{\frac{\sum_{i=1}^n (d_i - \bar{d})^2}{n}} \quad (3.23)$$

where

$$\bar{d} = \frac{1}{n} \sum_{i=1}^n d_i \quad (3.24)$$

Then by employing Chebyshev's inequality, we can calculate (i) the interval of an opponent's behavior according to any accuracy requirements; and (ii) the probability that any particular behavior may be performed by the opponent in the future. The Chebyshev inequality is given by Equation 3.25:

$$P(|X - \mu| \geq \varepsilon) \leq \frac{\sigma^2}{\varepsilon^2} \quad (3.25)$$

where  $X$  is an instance,  $\mu$  is the mathematical expectation,  $\sigma$  is the deviation, and  $\varepsilon$  is the accuracy requirement.

Equation 3.25 indicates the probability that the distance from a real offer  $\hat{u}_i$  to the estimated offer  $u_i$  is shorter than  $d_i$  and greater than  $\frac{\sigma^2}{\varepsilon^2}$ . So the probability that the opponent will generate a new offer within  $[\mu - d_i, \mu + d_i]$  in the future is  $1 - \frac{\sigma^2}{\varepsilon^2}$ .

By employing the three proposed regression functions and Chebyshev's inequality, an agent can estimate an opponent's possible negotiation behaviours in advance, and plan a suitable strategy as a response.



## 3.5 Experiments

In this section, we demonstrate three scenarios to test our proposed regression functions by comparing with the Tit-For-Tat and Random approaches. In order to simplify the implementation process, all agents in the experiment employ the NDF negotiation strategy [FWJ04a], and the alternating-offer protocol [Rub82]. Agents' negotiation behaviors cover all general possible situations, which are conceder, linear and boulware. During the negotiation, all agents employ the following function to generate offer in each negotiation round:

$$o^i = o^{ini} + (o^{res} - o^{ini}) \times \left(\frac{t_i}{\tau}\right)^\lambda + RE^i$$

where  $o^{ini}$  and  $o^{res}$  are an agent's initial and reservation offer respectively;  $t_i$  is the negotiation round;  $\tau$  is the negotiation deadline; and  $\lambda$  is the parameter to indicate an agent's negotiation strategy, such as conceder and linear. In order to simulate the real world, we also employ the factor Random Error ( $RE^i$ ) as a random number between  $-|o^{ini} - o^{res}| \times 5\%$  and  $|o^{ini} - o^{res}| \times 5\%$ .

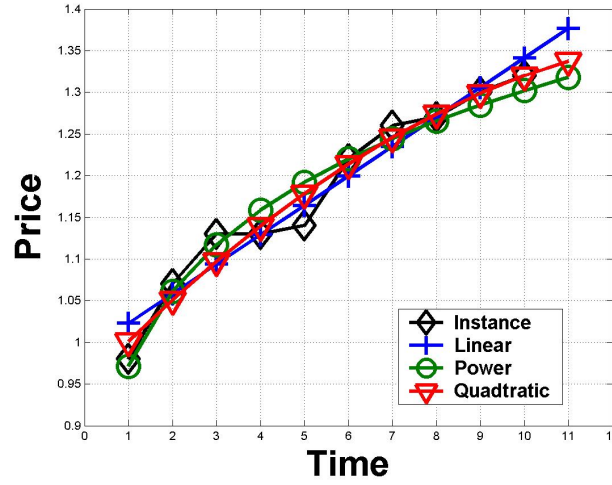
In the experiment, we use the average error ( $AE_k = \sum_{i=1}^k (\hat{u}_i - u_i)/k$ , where  $k$  is the total number of negotiation rounds) to evaluate the experimental results.  $AE_k$  indicates the difference between the estimated result and the real value. The smaller the value of  $AE_k$ , the better the prediction result.

### 3.5.1 Scenario 1

In the first scenario ( $S_1$ ), a buyer wants to purchase a mouse pad from a seller. The acceptable price for the buyer is in  $[\$0, \$1.4]$ . The deadline for the buyer to finish this negotiation is the 11<sup>th</sup> round. In this experiment, the buyer adopts Conceder negotiation behavior, and the seller employs the three proposed regression functions to estimate the buyer's price. The estimated results are displayed in Figure 3.2.

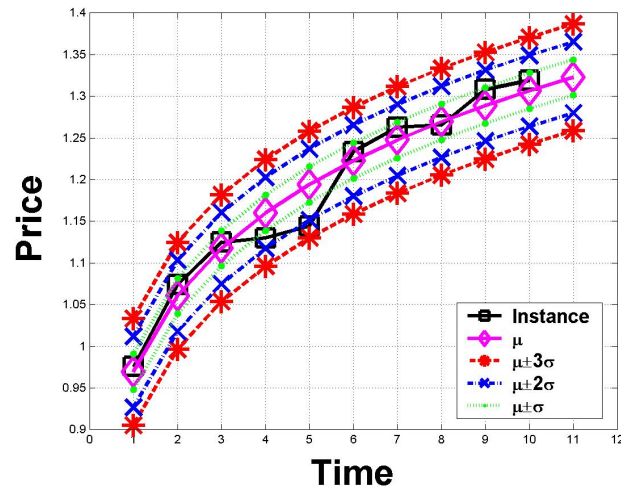
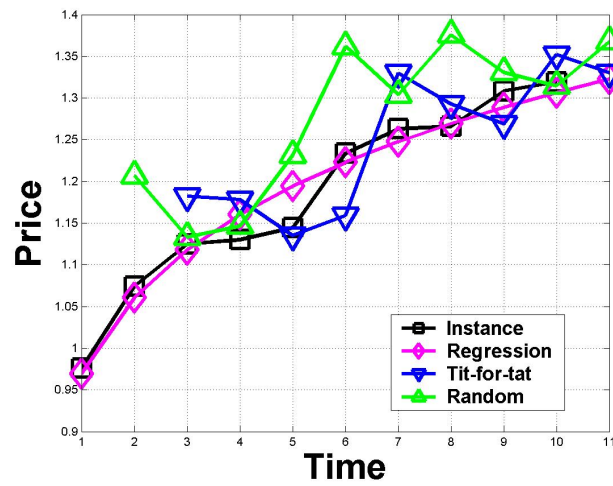
#### Linear Function

It can be seen that the linear approach dose not fit the instances very well, because it can only estimate the main trend of the buyer's offers but cannot provide more accurate values. The average error for the linear function is  $AE_{10}^l = 0.0189$ , which is 1.35% of the buyer's reservation price.

Figure 3.2: All Prediction results in  $S_1$ .

### Power Function

By contrast, the power approach provides more accurate prediction results. The estimated results for all negotiation rounds are displayed in Table 3.1. Each row in Table 3.1 illustrates the estimation result in each negotiation round in the form of estimated power regression function, estimation results ( $\mu$ ), and deviation ( $\sigma$ ). For example, it can be seen in the 7<sup>th</sup> round, the power regression approach estimates a price of \$1.26 from the buyer in the next round. Then according to the historical record in the 8<sup>th</sup> round, the real price given by the buyer in this round is \$1.27, which is very close to the estimated price. Figure 3.3 illustrates the situation in the last negotiation round. It can be seen that the accuracy of the estimation is very high because all estimated prices are in the interval  $[\mu - 2\sigma, \mu + 2\sigma]$  except during the 4<sup>th</sup> and 5<sup>th</sup> rounds, and all estimated results are almost exactly the same as the real prices. Figure 3.4 shows a comparison between the proposed approach and the other two estimation approaches, (Tit-For-Tat and Random ) in the last round. It can be seen that even though the Tit-For-Tat approach can follow the trend of the buyer's price changing, the errors (10% of the buyer's reservation price) are also large. The Random approach cannot even catch the main trend. The experimental results convince us that the proposed approach outperforms both the Tit-For-Tat and Random approaches when a buyer adopts conceder negotiation behaviors. The average error for the power approach is  $AE_{10}^p = 0.0165$ , which is 1.17% of the buyer's reservation price.

Figure 3.3: Power function prediction results in  $S_1$ .Figure 3.4: Power function prediction results comparison in  $S_1$ .

Round	Instance	Power regression function	Estimated $(\mu, \sigma)$
2	(0.98, 1.07)	price=0.98 $t^{0.14}$	(1.14, 0.00)
3	(0.98, 1.07, 1.12)	price=0.98 $t^{0.13}$	(1.17, 0.00)
4	(0.98, 1.07, 1.12, 1.13)	price=0.98 $t^{0.11}$	(1.17, 0.01)
5	(0.98, 1.07, 1.12, 1.13, 1.14)	price=0.99 $t^{0.10}$	(1.18, 0.02)
6	(0.98, 1.07, 1.12, 1.13, 1.14, 1.23)	price=0.98 $t^{0.11}$	(1.21, 0.02)
7	(0.98, 1.07, 1.12, 1.13, 1.14, 1.23, 1.26)	price=0.98 $t^{0.12}$	(1.25, 0.02)
8	(0.98, 1.07, 1.12, 1.13, 1.14, 1.23, 1.26, 1.27)	price=0.97 $t^{0.12}$	(1.26, 0.02)
9	(0.98, 1.07, 1.12, 1.13, 1.14, 1.23, 1.26, 1.27, 1.30)	price=0.97 $t^{0.13}$	(1.31, 0.02)
10	(0.98, 1.07, 1.12, 1.13, 1.14, 1.23, 1.26, 1.27, 1.30, 1.32)	price=0.97 $t^{0.13}$	(1.32, 0.02)

Table 3.1: Power function prediction results in  $S_1$ .

### Quadratic Function

The quadratic function's curve is in the middle of other two curves. The estimated results are displayed in Figure 3.5 and the regression function is:

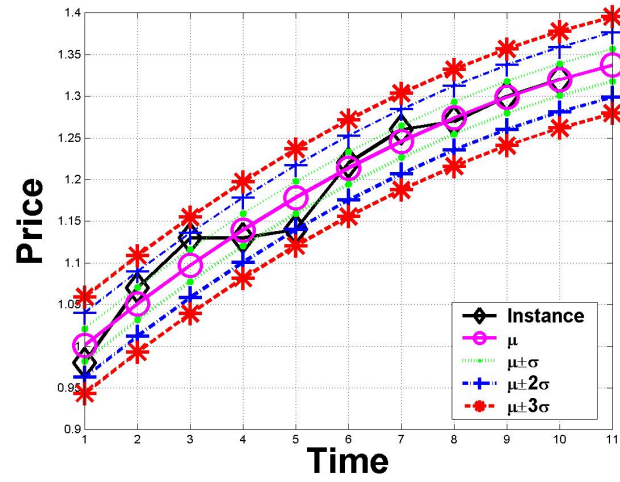
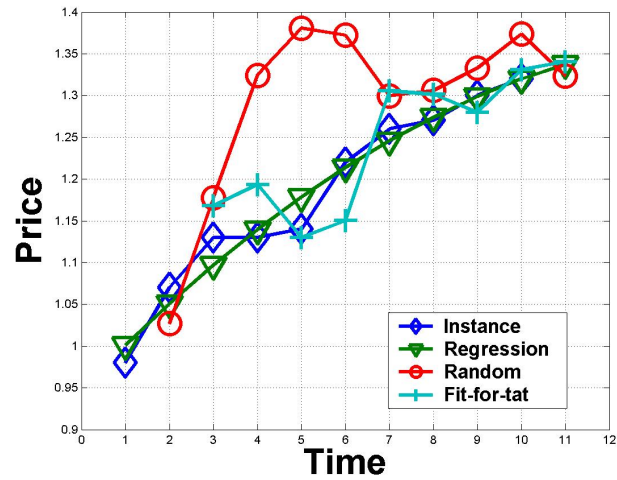
$$R(t) = -0.002 * t^2 + 0.055 * t + 0.948$$

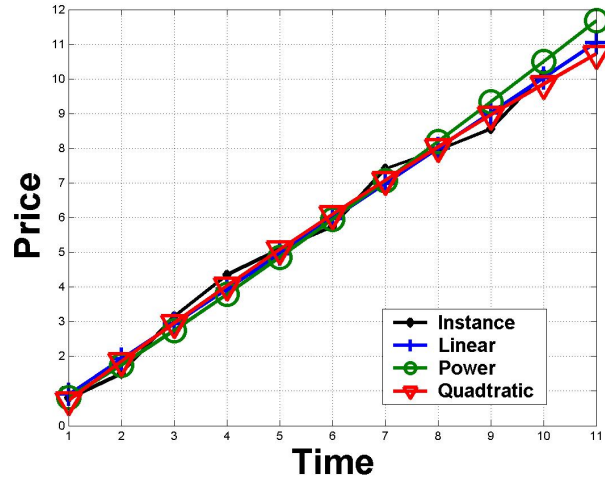
It can be seen that in the 8th negotiation round, the proposed approach estimates a price of \$1.26 from the buyer in the next round. Then according to the historical record in the 8th round, the real price given by the buyer is \$1.26, which is exactly the same as the estimation price. Furthermore, it can be seen that in rounds 4, 6, 9 and 10, the estimated prices are also the same as the real value. The estimated prices for the 2th, 3th and 7th rounds are \$1.05, \$1.10 and \$1.25 respectively, and the real prices given by the buyer in these rounds are \$1.07, \$1.13, and 1.26, which differ little from the estimated prices. According to Figure 3.5, all real prices are located in the interval  $[\mu - 2\sigma, \mu + 2\sigma]$ .  $AE_{10} = 0.015$ , which is only 1% of the buyer's reservation price. Therefore, the prediction results by employing the proposed quadratic approach are very reliable.

Figure 3.6 illustrates the comparison results between the quadratic approach and other two estimation approaches (Tit-For-Tat and Random). It can be seen that even though the Tit-For-Tat approach can follow the trend of changes in the buyer's price,  $AE_{10} = 0.078$ , which is five times that of our proposed approach. For the Random approach, it cannot even catch the main trend.  $AE_{10}$  for the random approach is 0.11, which is ten times more than our proposed approach. The experimental results convince us that the proposed quadratic approach significantly outperforms both the Tit-For-Tat and Random approaches when a buyer adopts Conceder negotiation behaviors.

#### 3.5.2 Scenario 2

In the second scenario ( $S_2$ ), a buyer wants to buy a keyboard from a seller. The acceptable prices for the buyer are in  $[\$0, \$14]$ . In this scenario, the buyer employs the Linear negotiation strategy, and the seller employs the proposed regression functions to estimate the buyer's offer. The prediction results are shown in Figure 3.7.

Figure 3.5: Quadratic function prediction results in  $S_1$ .Figure 3.6: Quadratic function prediction results comparison in  $S_1$ .

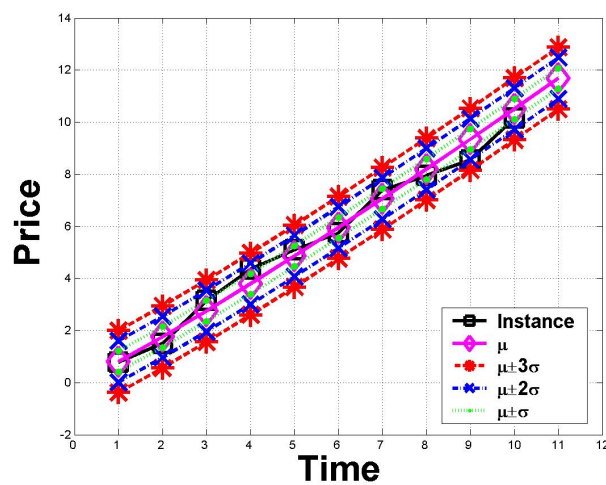
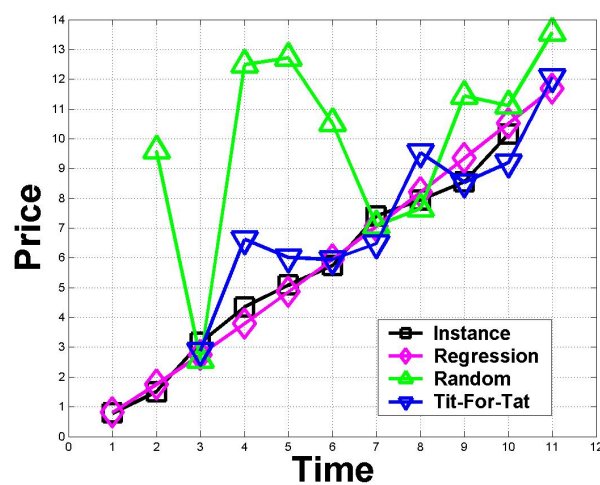
Figure 3.7: All prediction results in  $S_2$ .

### Linear Function

It can be seen that when the buyer employs the Linear negotiation strategy, the prediction results by using the linear function perform very well. The average error for the linear function is  $AE_{10}^l = 0.256$ , which is only 1.8% of the buyer's reservation price.

### Power Function

The estimated results by using the power function are displayed in Table 3.2 and Figure 3.8. It can be seen that the estimated power regression function also fits the real prices. In Figure 3.9, the comparison results among the Tit-For-Tat approach, Random approach and our proposed approach in the last negotiation round is illustrated. It can be seen that the overall error between the estimated prices and the real prices achieves the smallest value by employing the proposed approach, and achieve the largest value by employing the Random approach. Even the Tit-For-Tat approach can follow the buyer's trend, but distances between the estimated prices and the real prices are also very large. The experimental results demonstrate that when the buyer performs the linear negotiation strategy, the proposed power regression approach also outperforms both the Tit-For-Tat and Random estimation approaches.

Figure 3.8: Power function prediction results in  $S_2$ .Figure 3.9: Power function prediction results comparison in  $S_2$ .



Round	Instance	Power regression function	Estimated $(\mu, \sigma)$
2	(0.79, 1.50)	price= $0.79t^{0.94}$	(2.22, 0.00)
3	(0.79, 1.50, 3.15)	price= $0.74t^{1.23}$	(4.07, 0.21)
4	(0.79, 1.50, 3.15, 4.35,)	price= $0.74t^{1.26}$	(5.62, 0.18)
5	(0.79, 1.50, 3.15, 4.35, 5.09)	price= $0.75t^{1.22}$	(6.67, 0.24)
6	(0.79, 1.50, 3.15, 4.35, 5.09, 5.74)	price= $0.77t^{1.17}$	(7.50, 0.34)
7	(0.79, 1.50, 3.15, 4.35, 5.09, 5.74, 7.40,)	price= $0.77t^{1.17}$	(8.77, 0.31)
8	(0.79, 1.50, 3.15, 4.35, 5.09, 5.74, 7.40, 7.94)	price= $0.79t^{1.15}$	(9.89, 0.35)
9	(0.79, 1.50, 3.15, 4.35, 5.09, 5.74, 7.40, 7.94, 8.55)	price= $0.80t^{1.12}$	(10.55, 0.42)
10	(0.79, 1.50, 3.15, 4.35, 5.09, 5.74, 7.40, 7.94, 8.55, 10.15)	price= $0.81t^{1.11}$	(11.60, 0.40)

Table 3.2: Power function prediction results in  $S_2$ .

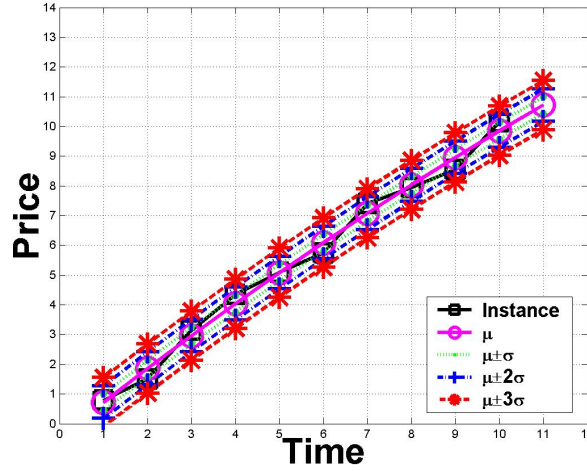


Figure 3.10: Quadratic function prediction results in  $S_2$ .

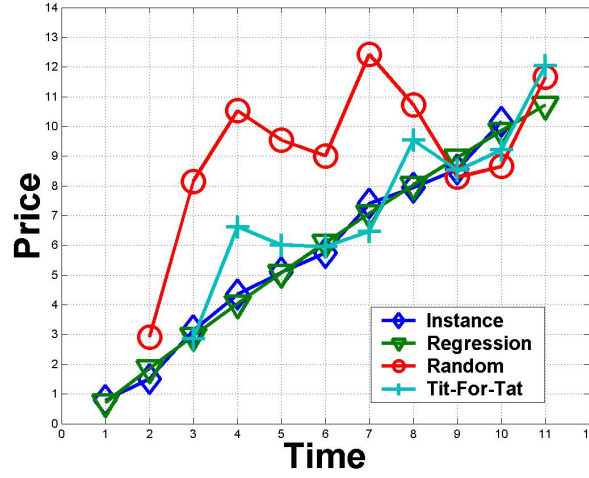
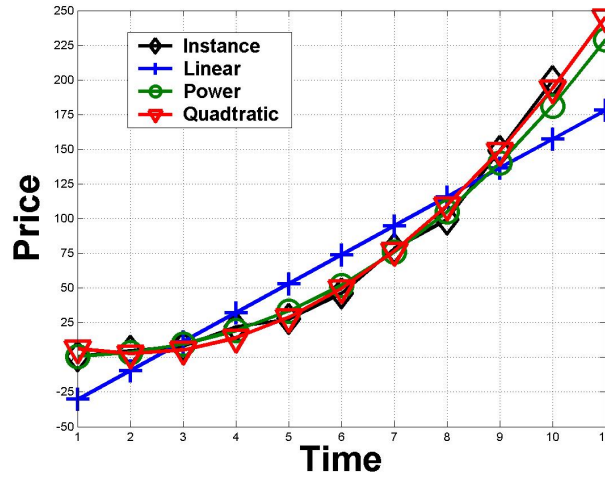
### Quadratic Function

The estimated results by employing the quadratic function are illustrated in Figure 3.10 and the estimated quadratic regression function is:

$$R(t) = -0.015 * t^2 + 1.178 * t - 0.439$$

It can be seen that in the 3th, 5th and 8th rounds, the estimated prices are exactly the same as the real offers given by the buyer. The biggest difference between the estimated price and the real price is just 0.4, which happens in the 9th round. The average error in this experiment is only  $AE_{10} = 0.24$ , which is no more than 2% of the buyer's reservation price. The estimated quadratic regression function fits the real prices very well.

In Figure 3.11, the comparison results among the Tit-For-Tat, Random and the quadratic approaches are illustrated. The average error for the Tit-For-Tat approach is  $AE_{10} = 2.52$ , namely 18% of the buyer's reservation price. The average error for the Random approach is very high, which is  $AE_{10} = 4.82$  and more than 34% of the buyer's reservation price. These experimental results demonstrate that when the buyer employs the Linear negotiation strategy, the proposed quadratic regression approach outperforms both the Tit-For-Tat and random approaches.

Figure 3.11: Quadratic function prediction results comparison in  $S_2$ .Figure 3.12: All prediction results in  $S_3$ .

### 3.5.3 Scenario 3

In the third scenario ( $S_3$ ), a buyer wants to purchase a monitor from a seller. The acceptable prices for the buyer are in  $[\$0, \$250]$  and the buyer employs the Boulware negotiation strategy. The prediction results are shown in Figure 3.12.

#### Linear Function

It can be seen that the linear approach performs much worse than other two proposed approaches. Actually, only one prediction result (at the 3<sup>rd</sup> round) in the linear function is the same as the real price from the buyer. The average error for the

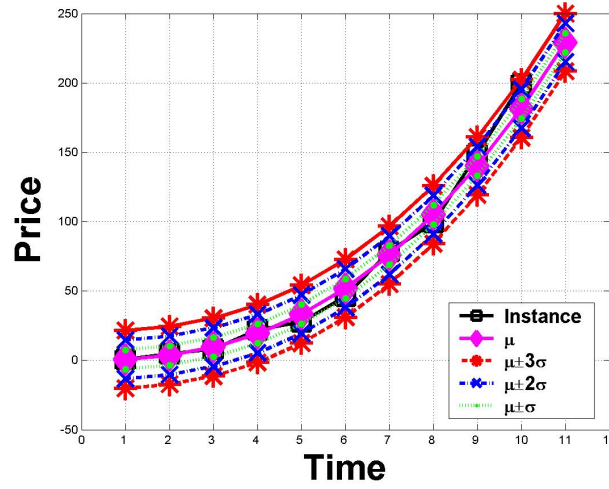


Figure 3.13: Power function prediction results in  $S_3$ .

linear regression function is  $AE_{10}^l = 19.872$ , which is 7.94% of the buyer's reservation price.

### Power Function

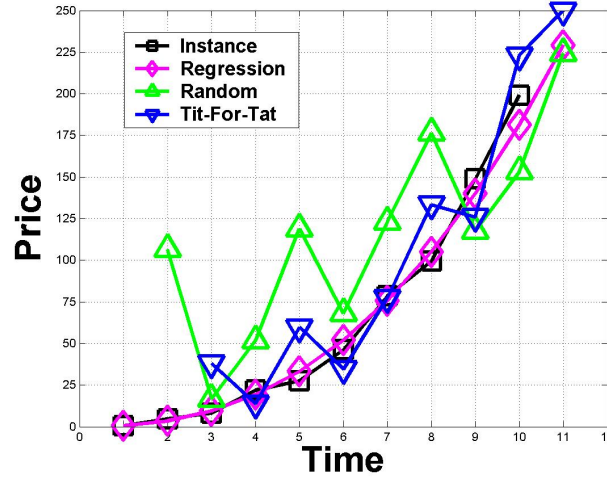
According to Table 3.3, the estimated price from the power regression function is  $price = 0.64 \times t^{2.45}$ . According to Figure 3.13, it can be seen that in the last negotiation round, the estimated price from the power function almost exactly fits all the real prices given by the buyer. Therefore, the seller could have sufficient reason to trust and adopt the estimation result for the next round. Finally, Figure 3.14 illustrates the comparison results with the Tit-For-Tat and Random estimation approaches. It can be seen that when the buyer adopts a Boulware behavior, the proposed power regression approach outperforms both the other two approaches. According to experimental results, the average error for the power regression function is  $AE_{10}^p = 5.196$ , which is only 2% of the buyer's reservation price.

### Quadratic Function

The quadratic regression function is:

$$R(t) = 3.038 * t^2 - 12.568 * t + 15.632$$

The estimated results by using the quadratic regression approach are shown in Figure 3.15. It can be seen that the proposed quadratic regression approach predicted buyer's prices successfully and accurately. Except in the 4th and 8th rounds,

Figure 3.14: Power function prediction results comparison in  $S_3$ .

Round	Instance	Power regression function	Estimated $(\mu, \sigma)$
2	(0.59, 4.71)	price= $0.59t^{3.01}$	(16.11, 0.00)
3	(0.59, 4.71, 8.06)	price= $0.65t^{2.45}$	(19.41, 1.11)
4	(0.59, 4.71, 8.06, 21.94)	price= $0.64t^{2.52}$	(36.95, 1.27)
5	(0.59, 4.71, 8.06, 21.94, 27.51)	price= $0.67t^{2.40}$	(49.39, 2.59)
6	(0.59, 4.71, 8.06, 21.94, 27.51, 46.12)	price= $0.68t^{2.38}$	(69.80, 2.36)
7	(0.59, 4.71, 8.06, 21.94, 27.51, 46.12, 78.45)	price= $0.67t^{2.41}$	(100.58, 3.50)
8	(0.59, 4.71, 8.06, 21.94, 27.51, 46.12, 78.45, 99.38)	price= $0.67t^{2.41}$	(133.60, 3.29)
9	(0.59, 4.71, 8.06, 21.94, 27.51, 46.12, 78.45, 99.38, 148.86)	price= $0.65t^{2.43}$	(174.95, 5.15)
10	(0.59, 4.71, 8.06, 21.94, 27.51, 46.12, 78.45, 99.38, 148.86, 199.08)	price= $0.64t^{2.45}$	(227.82, 6.95)

Table 3.3: Power function prediction results in  $S_3$ .

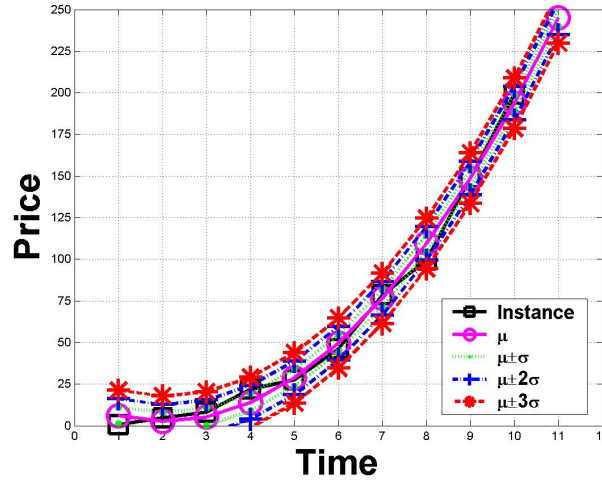


Figure 3.15: Quadratic function prediction results in  $S_3$ .

the estimated prices on the other rounds exhibit almost no difference with the buyer's real offers. The average error for the quadratic approach in this experiment is only  $AE_{10} = 4.07$ , which is only 1.6% of the buyer's reservation price. Therefore, we can say with confidence that from these estimation results, the seller can make very accurate judgement on the buyer's negotiation strategy, and make very reasonable responses in order to maximize its own benefit.

Finally, Figure 3.16 illustrates the comparison results with the Tit-For-Tat and Random approaches. For the Tit-For-Tat approach, the average error is  $AE_{10} = 57.74$ , which is 23% of the buyer's reservation price. For the Random approach, the average error is  $AE_{10} = 83.12$ , which is 33% of the buyer's reservation price. Therefore, it can be seen that when the agent performs Boulware behavior, the proposed quadratic regression approach outperforms both the Tit-For-Tat and Random approaches.

From the above experimental results, we can say that both the proposed power and quadratic regression functions can estimate an opponent's potential behaviors successfully, and the estimation results are also accurate and reasonable enough to be adopted by agents to modify their strategies in a negotiation. However, the linear regression function can only represent an opponent's behaviors when the negotiation strategy is Linear.

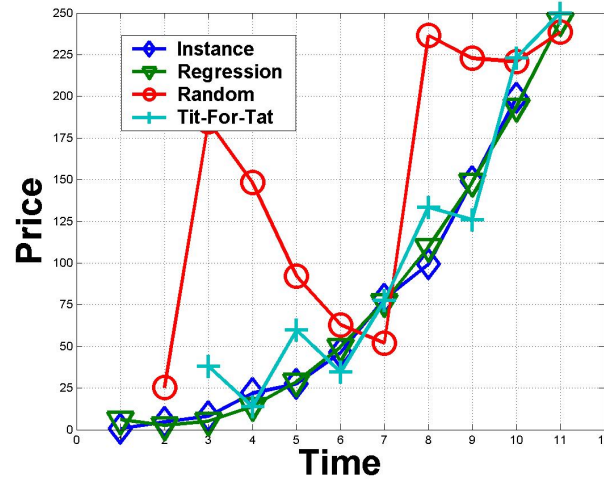


Figure 3.16: Quadratic function prediction results comparison in  $S_3$ .

## 3.6 Summary

In this chapter, we proposed three regression functions to estimate an opponent's negotiation behavior. We introduced the procedures to calculate the coefficients in each regression function, and the method to predict the opponent's possible behaviors. The experimental results demonstrate that the proposed approaches are novel and valuable to estimate an opponent's negotiation behavior.

# Chapter 4

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## Optimization of Bilateral Multiple Issue Negotiation

### 4.1 Introduction

In the previous chapter, an agent behavior prediction approach was introduced. However, when the number of negotiated issues becomes more than one, a new research problem appears. In [FWJ04b], Fatima et. al. pointed out that the procedure of multi-issue negotiation plays a critical role in determining the negotiation outcome. In general, there are three main procedures in multi-issue negotiation [FWJ06a], which are *package deal*, *simultaneous* and *sequential* procedure. In a *package deal*, all issues are bundled and discussed together; in a *simultaneous* procedure, all issues are discussed simultaneously but independent of each other; and in a *sequential* procedure, all issues are discussed one after another. By considering the time complexity and optimality, the *package deal* procedure is highly encouraged since it can outperform the two other procedures in most situations. In this chapter, we focus our attention on the *package deal* multi-issue negotiation procedure.

The most significant feature of multi-issue negotiation by use of the *package deal* procedure is that it may lead the negotiation results to mutually beneficial negotiation outcomes, i.e. both negotiation participators could receive benefits on their profits from the outcome, which otherwise cannot be achieved by single issue negotiation [LLS06, LSL07]. The mutually benefit can outcome makes multi-issue negotiation important and valuable in practice. Many researchers have paid attention to optimal negotiation outcome searching in multi-issue negotiation and some approaches have been successfully developed [FWJ04a, FWJ04b, FWJ06a]. However, most existing approaches mainly focus on static negotiation environments, in which negotiators predefine their preferences on negotiated issues and do not modify their preferences throughout the negotiation. After studying and analyzing peoples'



real behaviours in traditional markets on multiple issue bargaining, we noticed that usually people would like to modify their preferences during negotiation when the negotiation environment changes. Also, in electronic marketplaces, bargain hunters usually modify their preferences directly after the market information is updated. In order to successfully lead a negotiation result to a mutually benefit outcome, an optimal approach for multi-issue negotiation under time constraints in open and dynamic environments is proposed in this chapter.

The proposed approach contains three major steps, which are (i) opponent historical offers regression, (ii) opponent preferences estimation and (iii) optimal offer generation. In the first step, one or multiple quadratic regression function/s is/are generated to optimally fit opponents historical offers by extending the opponent behavior prediction approach introduced in Chapter 3. In the second step, an opponent's preference on all negotiated issues is predicted based on regression functions estimated in the first step. The preference estimation method in this step is based on a simple assumption that an opponent normally gives more concession to its low concern issues and less concession to its high concern issues. By analyzing differences between an opponent's concessions in all negotiated issues, the opponent's preferences on different issues can be estimated. In the third step, based on the estimation results on an opponent's preference, an optimal offer will be generated (if it is applicable) by employing the two proposed methods, which are the geometric method and the algebraic method, to benefit all negotiation participators.

The rest of this chapter is organized as follows. Section 4.2 extends the agent behavior prediction approach from a simple situation to a complex situation. Section 4.3 introduces a method to estimate an opponent's preference; Section 4.4 introduces two methods to dynamically generate mutually benefit offers based on current negotiation environment; Section 4.5 demonstrates experiments using the proposed approach and discusses experimental results; and Section 4.6 concludes this chapter.

## 4.2 Historical-Offer Regression

In this section, a historical offer regression method for multi-issue negotiation is introduced. It is an extended work based on Chapter 3.

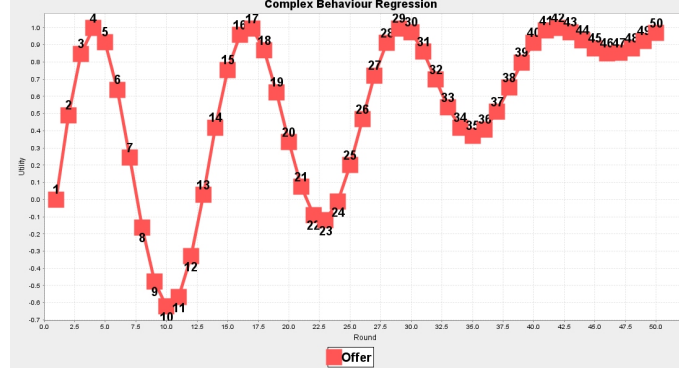


Figure 4.1: An example of complex agent behavior.

### 4.2.1 Complex Behaviors Prediction

In Chapter 3, we introduced four common agent behaviors in negotiation and proposed three regression functions to estimate agent negotiation behaviors. According to the experimental results, the quadratic regression function outperforms the other two functions. In this subsection, the quadratic regression function is extended to handle complex negotiation behaviors.

In multiple issue negotiation, agents may perform more complex behaviors than those four common behaviors introduced before. For example, agents may perform a Boulware negotiation strategy on one issue when the negotiation environment is disadvantageous to themselves, and change the strategy to Conceder when the environment improves. If the global utility for all issues does not change, an agent can modify its utilities on each individual issue. In Figure 4.1, we illustrate an example of a complex negotiation behavior. Obviously, such a complex behavior cannot be represented by a single quadratic regression function. In order to solve this issue, we introduce a multiple regression method to represent complex agent behavior.

The pseudocode of the multiple regression algorithm is displayed in Algorithm 1. The input of this algorithm is a negotiator's historical offers, and the output of this algorithm is a series of quadratic regression functions to optimally fit the negotiator's offers. Let  $\hat{\mathbf{U}}$  indicate the historical offers from an opponent,  $\mathbf{R}$  indicate the quadratic regression function set, and  $\tilde{\mathbf{U}}$  indicate a temporary set for calculation purpose. The basic procedure of the multiple regression algorithm is as follows.

**Step 1** Initialize both the regression data set  $\tilde{\mathbf{U}}$  and the regression function set  $\mathbf{R}$  to the empty set  $\emptyset$ ;

---

**Algorithm 1** Multiple Regression Algorithm.

---

**Input:** Historical utility set  $\hat{\mathbf{U}} = \{\hat{u}_t | t = 1 \dots T\}$ , and all  $\hat{u}_t$  have been normalized to  $[0, 1]$ . Threshold  $\lambda \in [0, 1]$ .

**Output:** Multiple regression function set  $\mathbf{R} = \{R_j(t) | j = 1 \dots J\}$ . Each regression function indicates a kind of behaviour performed by an agent in a certain period, and is in the form of  $R_j(t) = a_j \times t^2 + b_j \times t + c_j, t \in [t_j^{min}, t_j^{max}]$ .

**Initialization:** Initialize the set  $\tilde{\mathbf{U}}$  and  $\mathbf{R}$  to  $\emptyset$ .

**for** each utility  $\hat{u}_t$  in the set  $\hat{\mathbf{U}}$  **do**

$\tilde{\mathbf{U}} \leftarrow \tilde{\mathbf{U}} \cup \{\hat{u}_t\}$

**if** the size of  $\tilde{\mathbf{U}}$  is smaller than 2 **then**

go to the next iteration

**end if**

generate the quadratic regression function, namely  $R(t)$  by using the set  $\tilde{\mathbf{U}}$  and the regression approach introduced in Chapter 3.

initialize  $avg$  to 0

**for** each utility  $\hat{u}_t$  in the set  $\tilde{\mathbf{U}}$  **do**

$avg \leftarrow avg + |\hat{u}_t - u_t|^1$

**end for**

$avg \leftarrow \frac{avg}{sizeof(\tilde{\mathbf{U}})}$

**if**  $avg > \lambda$  **then**

reset the set  $\tilde{\mathbf{U}}$  to  $\emptyset$

$\mathbf{R} \leftarrow \mathbf{R} \cup \{R(t)\}$

**end if**

**end for**

return the set  $\mathbf{R}$

---

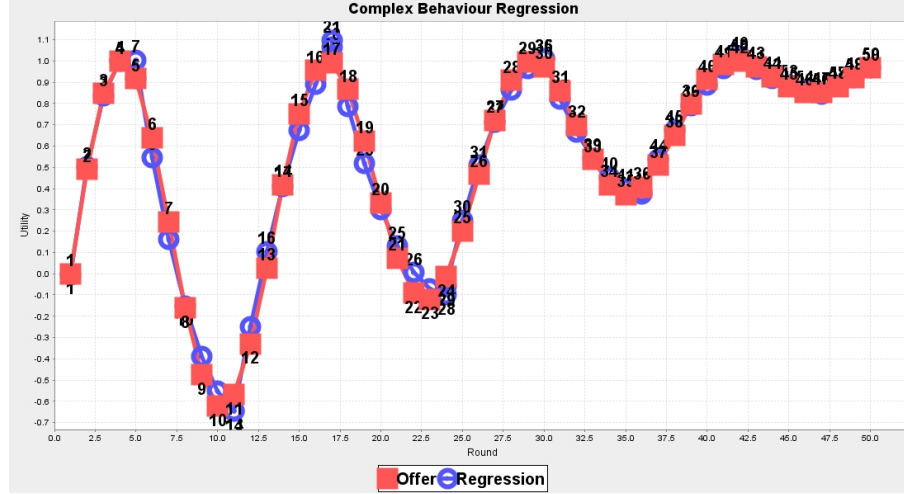


Figure 4.2: An example of multiple regression.

- Step 2** If the input set  $\hat{\mathbf{U}}$  is empty, then terminate the algorithm and output the set  $\mathbf{R}$ . Otherwise, move forward to **Step 3**;
- Step 3** Move a historical offer from the set  $\hat{\mathbf{U}}$  to the set  $\tilde{\mathbf{U}}$  according to the time series. If the size of set  $\tilde{\mathbf{U}}$  is smaller than 2, then repeat **Step 3**. Otherwise move forward to **Step 4**;
- Step 4** Generate a temporal regression function  $R(t)^*$  by using the dataset  $\tilde{\mathbf{U}}$  and the regression method introduced in Chapter 3;
- Step 5** Calculate the average distance between the historical offers in set  $\tilde{\mathbf{U}}$  and the regression results. If the average distance is smaller than a predefined value, then add the temporal function  $\tilde{R}(t)$  to the output set  $\mathbf{R}$ , empty the set  $\tilde{\mathbf{U}}$ , and move back to **Step 2**. Otherwise, move back to **Step 2** directly;

In Figure 4.2, we illustrate a regression result by applying the multiple regression algorithm on the example displayed in Figure 4.1. It can be seen that all regression functions fit the agent's complex behaviours very well. The regression functions generated by the multiple regression algorithm are listed in Table 4.1. From this example, we demonstrated that by employing the multiple regression algorithm, complex agent behaviours can also be represented by quadratic regression functions.

Table 4.1: Multiple quadratic regression functions.

Index	Regression Function	Round
1	$R(t) = -0.085 * t^2 + 0.59 * t - 0.004$	$t \in [1, 4]$
2	$R(t) = 0.037 * t^2 - 0.789 * t + 3.573$	$t \in [4, 11]$
3	$R(t) = -0.023 * t^2 + 0.87 * t - 7.097$	$t \in [11, 17]$
4	$R(t) = 0.024 * t^2 - 1.093 * t + 12.536$	$t \in [17, 24]$
5	$R(t) = -0.026 * t^2 + 1.551 * t - 21.76$	$t \in [24, 30]$
6	$R(t) = 0.017 * t^2 - 1.176 * t + 21.045$	$t \in [30, 36]$
7	$R(t) = -0.01 * t^2 + 0.869 * t - 17.745$	$t \in [36, 42]$
8	$R(t) = 0.004 * t^2 - 0.365 * t + 9.551$	$t \in [42, 47]$
9	$R(t) = 0.004 * t^2 - 0.355 * t + 8.396$	$t \in [47, 50]$

### 4.3 Preference Prediction

In this section, we introduce an approach to predict an opponent's preference in bilateral multi-issue negotiation. A *negotiation preference* indicates a negotiator's emphasis level on the negotiated issues when more than one negotiation issue is considered. Usually, a negotiation preference is represented linearly as a sequence of weight values [FWJ04b], and each weight value indicates a negotiator's concern on a particular issue. The greater/lower a weight value is assigned to an issue, the more/less concern will be paid to that issue. Let  $\mathbf{W}_t = \{w_t^m | m \in [1, M]\}$  ( $\sum_{m=1}^M w_t^m = 1$ ) be an opponent's preference on all negotiated issues, where  $w_t^m$  is the opponent's concern on the  $m^{th}$  issue, and  $M$  is the total number of issues in a multi-issue negotiation. In order to estimate the opponent's preference, firstly for each single issue  $m$  ( $m \in [1, M]$ ), we adopt the multiple quadratic regression algorithm introduced in the previous section to generate a set of regression functions  $\mathbf{R}^m = \{R_j^m(t) | j = 1 \dots J\}$  to specify the opponent's negotiation behaviors. Each  $R_j^m(t)$  is in the form of Equation 4.1.

$$R_j^m(t) = a_j^m \times t^2 + b_j^m \times t + c_j^m, t \in [t_{m,j}^{min}, t_{m,j}^{max}] \quad (4.1)$$

Now negotiators may have different preferences and may change their preferences when a negotiation environment changes. By consideration of the real world situation, we make the following assumption.

*A negotiator gives concessions to issues in a multi-issue negotiation based on its preference. The more/less significant an issue, the less/more concession will be given on the issue, and vice versa.*

For example, in a two-issue negotiation scenario, a buyer and a seller bargain

over a car's price and warranty. If the buyer is more concerned about the price, then he/she will give little concession on the price, but may make a large concession on the warranty. If the seller considers both the price and the warranty equally, then he/she will make similar concessions on the two negotiated issues. Based on the above assumption, we can inspect an opponent's historical offers on each issue and then predict the opponent's preference. Firstly, an opponent's modification on issue  $m$  at round  $t$  is represented by the derivative of the regression function  $R_j^m(t)$ , namely  $c_t^m$  ( $c_t^m \in C^m$ ).  $c_t^m$  is defined as follows.

$$\begin{aligned} c_t^m &= \frac{\text{partial} R_j^m(t)}{\text{partial} t} \\ &= 2a_j^m \times t + b_j^m \end{aligned} \quad (4.2)$$

It is noticed that the greater  $c_t^m$ , the less significant that issue  $m$  is considered by an opponent at round  $t$ , and the more concession the agent would like to give on the issue at round  $t$ . Let  $w_t^m$  ( $w_t^m \in \mathbf{W}_t$ ) be the opponent's concern on issue  $m$  at the round  $t$ ,  $w_t^m$  is calculated as follows.

$$\begin{aligned} w_t^m &= \frac{1/c_t^m}{\sum_{n=1}^M 1/c_t^n} \\ &= \frac{\prod_{n=1, n \neq m}^M c_t^n}{\sum_{n=1}^M (\prod_{p=1, p \neq n}^M c_t^p)} \end{aligned} \quad (4.3)$$

Then by calculating the opponent's concerns on all negotiated issues, ie.  $\mathbf{W}_t$ , the opponent's preference at round  $t$  is estimated.

## 4.4 Optimal Offer Generation

In this section, we introduce methods to generate an optimal offer in bilateral multi-issue negotiation by employing the predicted preference in the previous section.

Before introducing the proposed methods, we firstly define some notations. Let Agents  $p$  and  $q$  be the two negotiators. For one agent (either Agent  $p$  or  $q$ ), we assume that it already knew its own negotiation strategy, utility function and preference at any particular negotiation round  $t$ , namely  $\lambda_t$ ,  $U(t)$  and  $\mathbf{W}_t = \{w_t^m | m = 1 \dots M\}$  ( $\sum_{m=1}^M w_t^m = 1$ ), respectively. Secondly, by employing the prediction method introduced in section 4.3, the agent can estimate its opponent's preference at round

$t$ , namely  $\mathbf{W}_t^o = \{w_t^{o,m} | m = 1 \dots M\}$  ( $\sum_{m=1}^M w_t^{o,m} = 1$ ). Furthermore, according to the “pie splitting” theory [Rub82], if the whole utility of an item is 1 and one negotiator claims  $u$  ( $u \in [0, 1]$ ) out of 1, then the other negotiator’s utility is  $1 - u$ . In multi-issue negotiation, the situation on each single issue can be treated similar as the “pie splitting” game, ie. if an agent claims  $u_t^m$  utility for issue  $m$  at the round  $t$ , then its opponent can only get  $(1 - u_t^m)$  utility.

Let set  $\mathbf{U}_t = \{u_t^m | m = 1 \dots M, u_t^m \in [0, 1]\}$  be an agent’s utilities on all issues at round  $t$  according to its utility function  $U(t)$ . Normally, for any negotiation round  $t$ ,  $u_t^m = U(t)$  and  $\sum_{m=1}^M u_t^m \times w_t^m = U(t)$ . Let set  $\mathbf{U}_t^* = \{u_t^{m*} | m = 1 \dots M, u_t^{m*} \in [0, 1]\}$  be an agent’s utilities on all issues at round  $t$  by adopting the optimal offer. Then the purpose of this chapter is to find the set  $\mathbf{U}_t^*$  which benefits all negotiation participators, i.e. maximizing an agent’s utility and also increasing the opponent’s loss as much as possible. Let Inequality 4.4 indicate such a requirement for the optimal offer  $\mathbf{U}_t^*$  as follows.

$$\begin{cases} \sum_{m=1}^M u_t^{m*} \times w_t^m \geq \sum_{m=1}^M u_t^m \times w_t^m & (a) \\ \sum_{m=1}^M (1 - u_t^{m*}) \times w_t^{o,m} \geq \sum_{m=1}^M (1 - u_t^m) \times w_t^{o,m} & (b) \end{cases} \quad (4.4)$$

Equation 4.4 indicates that the optimal offer  $\mathbf{U}_t^*$  should provide more utility to both negotiation participators than an agent’s original offer  $\mathbf{U}_t$ . In order to solve this problem, firstly, we transform Inequality 4.4 to Inequality 4.5, then we will introduce two methods, i.e. a geometric method and an algebraic method, in the following two subsections to solve the problem.

$$\begin{cases} \sum_{m=1}^M u_t^{m*} \times w_t^m - \sum_{m=1}^M u_t^m \times w_t^m \geq 0 & (a) \\ \sum_{m=1}^M u_t^{m*} \times w_t^{o,m} - \sum_{m=1}^M u_t^m \times w_t^{o,m} \leq 0 & (b) \end{cases} \quad (4.5)$$

#### 4.4.1 A Geometric Method

In this subsection, we introduce a geometric method to calculate the solution for Inequality 4.5, and try to equally increase both negotiators’ utilities. In order to simplify the discussion, we specify the size of negotiation issues to two ( $M = 2$ ). Then Inequality 4.5 can be rewritten as follows:

$$\begin{cases} w_t^1 \times u_t^{1*} + w_t^2 \times u_t^{2*} - u_t \geq 0 & (a) \\ w_t^{o,1} \times u_t^{1*} + w_t^{o,2} \times u_t^{2*} - (1 - u_t^o) \leq 0 & (b) \end{cases} \quad (4.6)$$

where

$$\begin{cases} u_t = w_t^1 \times u_t^1 + w_t^2 \times u_t^2 \\ u_t^o = w_t^{o,1} \times (1 - u_t^1) + w_t^{o,2} \times (1 - u_t^2) \end{cases} \quad (4.7)$$

Let the  $x$ -axis indicate an negotiator's utility on issue 1, and the  $y$ -axis an negotiator's utility on issue 2, then some possible situations of Inequality 4.6 are illustrated in Figure 4.3. Let Line  $A$  be the line indicated by the function  $w_t^1 \times u_t^{1*} + w_t^2 \times u_t^{2*} - u_t = 0$  and Line  $B$  be the line indicated by the function  $w_t^{o,1} \times u_t^{1*} + w_t^{o,2} \times u_t^{2*} - (1 - u_t^o) = 0$ , then Line  $A$  indicates an agent's utility function at negotiation round  $t$ , and Line  $B$  indicates an opponent's utility function. Let Point  $P$  (if it is applicable) be the interaction between Line  $A$  and Line  $B$ , then Point  $P$  is a solution to satisfy Inequality 4.6. However, because negotiators may have different preferences, it is possible to find other points to increase both negotiators' utilities together.

According to the geometric meaning of Inequality 4.6, a point located above Line  $A$  will enlarge an agent's utility, and a point located below Line  $B$  will enlarge an opponent's utility. If we can find a point, namely Point  $O$ , which is located above Line  $A$  as well as below Line  $B$ , then both negotiators' utilities can be increased at the same time. The distance between Point  $O$  and Line  $A/B$  indicates the increment on an agent's/opponent's utility. Theoretically, more than one point (if this is applicable) may be found to increase both negotiators' utilities, in order to equally and maximally enlarge both negotiators utilities. We consider three possible cases, which are (i) Line  $A$  and Line  $B$  are not parallel, (ii) Line  $A$  and Line  $B$  are parallel, and (iii) Line  $A$  and Line  $B$  are identical. We will discuss the existence of Point  $O$  and the approach to calculate Point  $O$  (if it is applicable) in each case.

Before we start the discussion on the three possible cases, some useful points which may help us to solve the problem are firstly defined. Let Point  $Ax$  be the intersection between Line  $A$  and the  $x$ -axis, and Point  $Ay$  be the intersection between Line  $A$  and the  $y$ -axis. Let Point  $Bx$  be the intersection between Line  $B$  and the  $x$ -axis, and Point  $By$  be the intersection between Line  $B$  and the  $y$ -axis, then Points  $Ax$ ,  $Ay$ ,  $Bx$ ,  $By$ , and  $P$  are defined as follows.



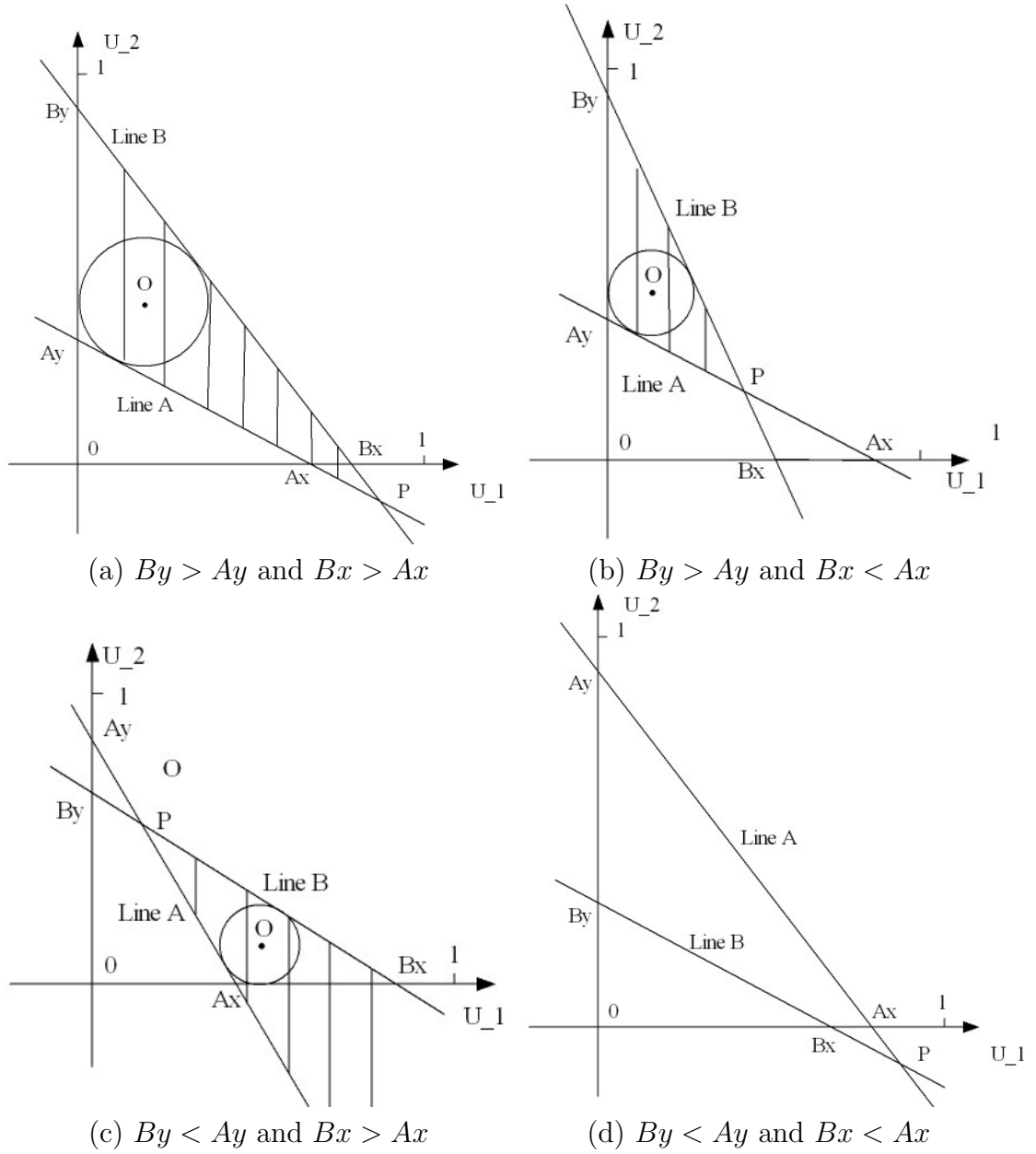


Figure 4.3: Lines A and B have an intersection.

$$\begin{cases} Ax = (\frac{u_t}{w_t^1}, 0) \\ Ay = (0, \frac{u_t}{w_t^2}) \\ Bx = (\frac{1-u_t^o}{w_t^{o,1}}, 0) \\ By = (0, \frac{1-u_t^o}{w_t^{o,2}}) \\ P = (\frac{u_t w_t^{o,2} - w_t^2 (1-u_t^o)}{w_t^1 w_t^{o,2} - w_t^2 w_t^{o,1}}, \frac{w_t^1 (1-u_t^o) - u_t w_t^{o,1}}{w_t^1 w_t^{o,2} - w_t^2 w_t^{o,1}}) \end{cases} \quad (4.8)$$

### Line A and Line B are not Parallel

If Line A and Line B are not parallel, in order to equally and maximally increase both negotiators' utilities, we propose that Point O is the center of the inscribed circle of triangle  $P - Ay - By$  (if  $Ay < By$ ) or triangle  $P - Ax - Bx$  (if  $Ax < Bx$ ). The reason behind such a proposal is that the center of the inscribed circle has maximal and equal distance to the three edges of the triangle, which indicates both negotiators' utilities can be equally maximized. In Figure 4.3, we illustrate four possible cases when Line A and Line B intersect. For the cases illustrated in Figure 4.3(a)-(c), if the three vertices of the triangle are located at point  $(x_a, y_a)$ , point  $(x_b, y_b)$  and point  $(x_c, y_c)$ , and the opposite sides of the triangle have lengths  $a$ ,  $b$ , and  $c$ , then the incenter is at point  $O(o_x, o_y)$ . Point O can be calculated by Equation 4.9. For the case illustrated in Figure 4.3(d), if Point P is out of the first quadrant and  $Ay > Ax$ , because Line A is located above Line B in the first quadrant, it is not possible to find the Point O to increase both negotiators' utilities together.

In general, if Line A and Line B intersect, this means that both negotiators have (1) different preferences on the negotiation issues, and (2) different acceptance areas on the negotiation outcome, and Line A and Line B will have different slopes and different intersections with the  $x$ -axis and  $y$ -axis. For example, in a two-issue negotiation related to a car's price and warranty, a buyer's initial offer on the two issues is (\$4000, 5years), reservation offer is (\$5500, 2years) and the preference on the two issues is (0.7, 0.3). On the other hand, a seller's initial offer is (\$6000, 3years), the reservation offer is (\$5000, 4years), and the seller's preference is (0.5, 0.5). Because the seller and the buyer have different considerations on both the preference and acceptance areas of the two negotiated issues, Point O exists and can be determined by employing Equation 4.9.

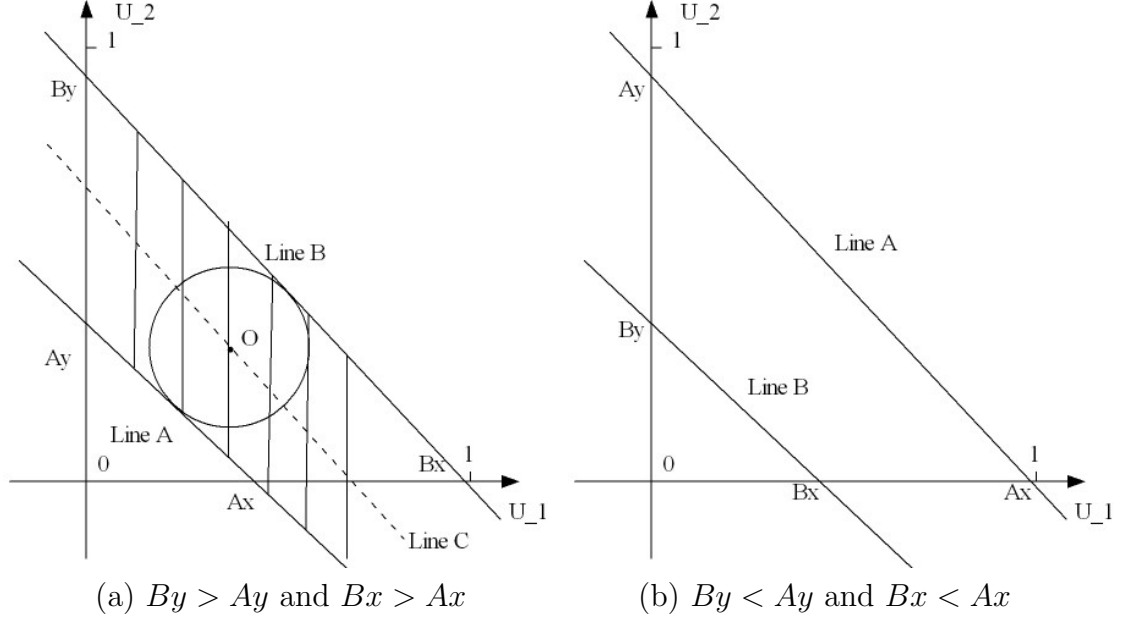


Figure 4.4: Lines A and B do not have an intersection.

$$\begin{cases} o_x = \frac{ax_a + bx_b + cx_c}{a+b+c} \\ o_y = \frac{ay_a + by_b + cy_c}{a+b+c} \end{cases} \quad (4.9)$$

where

$$\begin{cases} a = \sqrt{(x_b - x_c)^2 + (y_b - y_c)^2} \\ b = \sqrt{(x_c - x_a)^2 + (y_c - y_a)^2} \\ c = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2} \end{cases} \quad (4.10)$$

### Line A and Line B are Parallel

If Line A and Line B do not intersect, then Line A may be located below or above Line B. If Line A is located below Line B, according to Figure 4.4(a), any point on the middle line (Line C) between Line A and Line B can be the optimal point. However, in order to decrease the impact caused by inaccurately estimating the opponent's utility function and preference, we set the middle point on Line C as the Point  $O(o_x, o_y)$  as follows.

$$\begin{cases} o_x = \frac{Ax_x + Bx_x}{4} \\ o_y = \frac{Ay_y + By_y}{4} \end{cases} \quad (4.11)$$

where  $Ax_x$  and  $Bx_x$  are the  $x$ -axis values of Points  $Ax$  and  $Bx$ , and  $Ay_y$  and  $By_y$  are the  $y$ -axis value of Point  $Ay$  and  $By$ , respectively.

For the case illustrated in Figure 4.4(b), because Line  $A$  is located above Line  $B$ , it is impossible to find a point located above Line  $A$  as well as below Line  $B$ , so the Point  $O$  does not exist. In general, if Line  $A$  and Line  $B$  are parallel, this means that both negotiation participants have a similar preference on negotiated issues but different acceptance areas on the negotiation outcome. Let us use the example in Subsection 4.4.1 again. If the seller modifies its preference to  $(0.7, 0.3)$ , which is the same as the buyer's preference, then Line  $A$  and Line  $B$  will be parallel. Nevertheless, because both negotiators have different acceptance areas on the negotiation outcome, the optimal offer still exists. However, as shown in Figure 4.4, if negotiators' acceptance areas do not intersect, an optimal offer does not exist.

#### Line $A$ and Line $B$ are Identical

If Line  $A$  and Line  $B$  are identical, it is impossible to find the Point  $O$  to benefit all negotiators. When Line  $A$  and Line  $B$  are identical, this indicates that both negotiation participants have a similar preference, and also the same acceptance area on the negotiation outcome. Taking the example we used before, if the seller modifies its initial offer to  $(\$5500, 2years)$ , its reservation offer to  $(\$4000, 5years)$ , and its preference to  $(0.7, 0.3)$ , the seller and buyer will have the same preference and acceptance area on the negotiation outcome, then the offer to benefit both negotiators at the same time does not exist.

In summary, for the four cases discussed above, if Point  $O$  exists, by setting  $u_t^{1*}$  to the  $x$ -axis value of Point  $O$  and  $u_t^{2*}$  to the  $y$ -axis value of Point  $O$ , the optimal offer for an agent at round  $t$  is generated. However, if Point  $O$  does not exist, we can only adopt the original offer, i.e.  $u_t^1 = u_t^2 = U(t)$ .

### 4.4.2 An Algebraic Method

The geometric method introduced in the previous subsection might be hard to implement when the number of negotiated issues is greater than three. In this subsection,

we introduce an algebraic method to calculate the optimal offer.

The principle of the algebraic method is as follows. Generally, it is proposed that an agent's optimal offer at round  $t$  should satisfy two requirements. (i) The optimal offer should maximize an agent's profit as much as possible. The reason behind this requirement is based on the consideration that all negotiators in a bargain situation are selfish and seek maximal benefits [Kra01]. Also (ii) the optimal offer should minimize an opponent's loss. The reason behind this consideration is based on the situation that an opponent will not accept an offer which damages its benefit too much. In order to make an optimal offer more acceptable for an opponent so as to increase the negotiation efficiency, the second requirement should also be satisfied as much as possible.

In order to find out the optimal offer by using an algebraic method, we employ Lagrange Multipliers. The purpose of Lagrange Multipliers is to try to maximize a function  $f(\mathbf{x})$  by considering a constraint  $g(\mathbf{x}) = c$ , where  $\mathbf{x}$  indicates variables and  $c$  is a constant.

Let Equation 4.12(a) be an agent's increment on utility after employing the optimal offer  $\mathbf{U}_t^*$  at round  $t$ , then Equation 4.12(a) is the function that the agent tries to maximize. Let Equation 4.12(b) be an opponent's loss on utility if it accepts the optimal offer  $\mathbf{U}_t^*$ , then Equation 4.12(b) is the constraint that the agent tries to satisfy. We use variable  $c$  to indicate the amount of possible loss for the opponent. In order to minimize the opponent's loss, we set the default value of  $c$ 's to 0. If an optimal offer does not exist under such a constraint, the constraint will be relaxed according to a predefined criteria. For example, the constraint can be enlarged gradually by 0.1 until an optimal offer is achieved or until,  $c = 1$ . Based on the above consideration, we let 4.12(a) be the  $f(\mathbf{x})$  function in a Lagrangian and 4.12(b) be the  $g(\mathbf{x})$  function in the Lagrangian, then in order to find the optimal offer  $\mathbf{U}_t^*$ , the Lagrangian is defined in Equation 4.13.

$$\begin{cases} f(\mathbf{U}_t^*) = \sum_{m=1}^M u_t^{m*} \times w_t^m - \sum_{m=1}^M u_t^m \times w_t^m & (a) \\ f^o(\mathbf{U}_t^*) = \sum_{m=1}^M u_t^{m*} \times w_t^{o,m} - \sum_{m=1}^M u_t^m \times w_t^{o,m} & (b) \end{cases} \quad (4.12)$$

where  $\mathbf{U}_t^* = \{u_t^{m*} | m = 1 \dots M\}$ .

$$\Lambda(\mathbf{U}_t^*, \lambda) = f(\mathbf{U}_t^*) + \lambda \times (f^o(\mathbf{U}_t^*) - c) \quad (4.13)$$

Firstly, by setting the partial derivative for  $\Lambda(\mathbf{U}_t^*, \lambda)$  on each variable in set  $\mathbf{U}_t^*$  and  $\lambda$  to zero, respectively, we can obtain Equation (4.14) as follows:

$$\left\{ \begin{array}{l} \frac{\partial \Lambda(\mathbf{U}_t^*, \lambda)}{\partial u_t^{1*}} = \frac{\partial f(\mathbf{U}_t^*)}{\partial u_t^{1*}} + \lambda \times \frac{\partial f^o(\mathbf{U}_t^*)}{\partial u_t^{1*}} = 0 \\ \vdots \\ \frac{\partial \Lambda(\mathbf{U}_t^*, \lambda)}{\partial u_t^{m*}} = \frac{\partial f(\mathbf{U}_t^*)}{\partial u_t^{m*}} + \lambda \times \frac{\partial f^o(\mathbf{U}_t^*)}{\partial u_t^{m*}} = 0 \\ \vdots \\ \frac{\partial \Lambda(\mathbf{U}_t^*, \lambda)}{\partial u_t^{M*}} = \frac{\partial f(\mathbf{U}_t^*)}{\partial u_t^{M*}} + \lambda \times \frac{\partial f^o(\mathbf{U}_t^*)}{\partial u_t^{M*}} = 0 \\ \frac{\partial \Lambda(\mathbf{U}_t^*, \lambda)}{\partial \lambda} = f^o(\mathbf{U}_t^*) - c = 0 \end{array} \right. \quad (4.14)$$

Equation (4.14) contains  $M + 1$  variables and formulas, and by solving Equation (4.14), we may get three possible results, which are:

1. No solution. Then we can enlarge an opponents' losses (the value of  $c$ ) according to a predefined criteria and recalculate the optimal offer;
2. A single solution  $\mathbf{U}_t^* = \{u_t^{m*} | m = 1 \dots M\}$ , where  $u_t^{m*}$  indicates the offer on the  $m^{th}$  issue. Then  $\mathbf{U}_t^*$  is the optimal solution;
3. Multiple solutions, namely set  $\mathbf{MU}_t^* = \{\mathbf{U}_{t,i}^*\}$ . Then the optimal solution  $\mathbf{U}_t^*$  can be found as follows:

$$\forall \mathbf{U}_{t,i}^* \in \mathbf{MU}_t^*, \exists \mathbf{U}_t^* \in \mathbf{MU}_t^* \Rightarrow f(\mathbf{U}_t^*) \geq f(\mathbf{U}_{t,i}^*) \quad (4.15)$$

### 4.4.3 Discussion

In this section, we introduced a geometric and an algebraic method to generate the optimal offer in bilateral multi-issue negotiation. According to our studies, both proposed methods have advantages and disadvantages.

For the geometric method, the advantage is that an optimal solution for a negotiation can be intuitively illustrated by a graph. However, when the number of negotiated issues is greater than three, the calculation cost for the optimal offer will become huge because of the large number of possible cases on relationships between the two negotiators' preferences and acceptable outcome areas.

For the algebraic method, the advantage that it can handle negotiations which contain more than three issues. However, the disadvantage is that the selection of constraint value will impact the negotiation outcome. An agent needs to carefully

choose the constraint value in order to reach the optimal outcome effectively and efficiently.

Therefore, an agent should choose a suitable method to calculate the optimal offer according to its own specification and requirement in an application domain. However, no matter which method is selected by an agent, during a negotiation, both negotiators can employ the proposed methods alternately until an agreement is accepted by all negotiators, or one negotiator quits the negotiation. Also, by analyzing the optimal offers in different cases, we make the following discovery:

*In a multi-issue negotiation, the possibility that a negotiator can increase its utility from an optimal offer is impacted by the difference between the negotiator's and the opponent's preferences. The greater/smaller the difference, the more/less possibility that the negotiator's utility can be increased by the optimal offer.*

The proof of the above discovery is as follows:

Let  $d_t^m = w_t^m - w_t^{o,m}$ ,  $m \in [1, M]$  be the difference between an agent's and the opponent's preferences on issue  $m$  at round  $t$ , then Equation 4.5 can be written as follows:

$$\begin{cases} \sum_{m=1}^M u_t^{m*} \times w_t^m - \sum_{m=1}^M u_t^m \times w_t^m \geq 0 & (a) \\ \sum_{m=1}^M u_t^{m*} \times (w_t^m - d_t^m) - \sum_{m=1}^M u_t^m \times (w_t^m - d_t^m) \leq 0 & (b) \end{cases} \quad (4.16)$$

which can be transformed to,

$$\begin{cases} \sum_{m=1}^M u_t^{m*} \times w_t^m - \sum_{m=1}^M u_t^m \times w_t^m \geq 0 & (a) \\ \sum_{m=1}^M u_t^{m*} \times w_t^m - \sum_{m=1}^M u_t^m \times w_t^m \leq \sum_{m=1}^M d_t^m \times (u_t^{m*} - u_t^m) & (b) \end{cases} \quad (4.17)$$

Obviously, if the agent and the opponent have the same preference, i.e.  $d_t^m = w_t^m - w_t^{o,m} = 0$ ,  $m \in [1, M]$ , then the only possible solution for Equation 4.17 is  $\sum_{m=1}^M u_t^{m*} \times w_t^m - \sum_{m=1}^M u_t^m \times w_t^m = 0$ , which means the proposed optimal offer  $\mathbf{U}_t^*$  cannot enlarge any negotiator's utility at all. On the other hand, if any  $d_t^m \neq 0$  ( $m \in [1, M]$ ), i.e. the agent and the opponent have a different preference, then it is highly possible that the optimal offer  $U_t^*$  can maximize  $\sum_{m=1}^M d_t^m \times (u_t^{m*} - u_t^m)$ . So the possibility that a negotiator can increase its utility by adopting the optimal solution  $\mathbf{U}_t^*$  is impacted by the difference between two negotiator's preferences.

## 4.5 Experiment

In this section, we examine our proposed bilateral multi-issue negotiation approach through comparison with the NDF negotiation approach [FWJ04a].

### 4.5.1 Experimental Setup

All experiments are performed on a DELL OPTIPLEX GX620 machine. In order to simplify the experiments, we employ three agents (one seller and two buyers) in a two-issue negotiation. Because the proposed geometric optimization method can easily handle two-issue negotiation and can illustrate the negotiation outcome by a 2-D graph, we will adopt the geometric optimization method in experiments. Of course, agents can choose either the geometric method or the algebraic method, according to their specifications and applications. The correctness of the algebraic method was proved mathematically in Subsection 4.4.2.

The experimental setup is described as follows: A seller agent *seller1* wants to sell a car and also provides warranty for a number of years, and both buyer agents *buyer1* and *buyer2* want to purchase the car from *seller1*. In order to make the negotiation results more reliable, the buyer agent and the seller agents adopt different initial offers, reservation offers, preferences, negotiation strategies, deadlines. Also, in order to make the negotiation results more comparable, two buyer agents (i.e. *buyer1* and *buyer2*) adopt the same negotiation parameters during the negotiation. All negotiators' parameters are listed in Table 4.2. More specifically, the buyer's initial price is randomly selected within [\$1600, \$2400], and the initial warranty is randomly selected within [4years, 6years]. The buyer's reservation price is randomly selected within [\$2400, \$3600], and the buyer's reservation warranty is randomly selected within [2.4years, 3.6years]. In order to ensure both negotiation participants have an agreement zone, the seller's initial offer is set to the buyer's reservation offer, and the seller's reservation offer is set to the buyer's initial offer. All negotiators' negotiation strategies are randomly selected among the *Boulware*, *Conceder* and *Linear* negotiation strategies. The negotiation deadlines are randomly selected within [16, 24] rounds, and all agents' preferences are also generated randomly.

During the negotiation, all agents employ Rubinstein's alternating offer protocol [Rub82] as the negotiation protocol and the *package deal procedure* as the negotiation procedure. All agents keep their negotiation parameters privately. In order



Table 4.2: Negotiation parameters.

Agent Name	Initial Offer		Reserved Offer		Preference	
	Price	Warranty	Price	Warranty	Price	Warranty
<i>Buyer 1 and 2</i>	[\$1600, \$2400]	[4y, 6y]	[\$2400, \$3600]	[2.4y, 3.6y]	[0, 1]	[0, 1]
<i>Seller 1</i>	[\$2400, \$3600]	[2.4y, 3.6y]	[\$1600, \$2400]	[4y, 6y]	[0, 1]	[0, 1]
<i>Buyer 1 and 2</i> <i>Seller 1</i>	Strategy		Deadline		PMP	
	[0, 2]		[16, 24]		0%	
	[0, 2]		[16, 24]		[0%, 100%]	

to simulate an open and dynamic negotiation environment, *seller1* will randomly modify its preference. The probability that *seller1* will modify **its** preference is indicated by the factor Probability Modify Preference (PMP). The value of PMP is randomly selected between [0%, 100%]. If  $PMP = 0\%$ , this indicates that *seller1* will not modify its preference at all. If  $PMP = 50\%$ , this indicates that *seller1* has 50% likelihood of modifying its preference. Also if  $PMP = 100\%$ , this indicates that *seller1* will definitely modify its preference in each negotiation round. Let  $w_p$  indicate *seller1*'s concern on the price, and  $w_w$  indicate *seller1*'s concern on the warranty, then a preference is generated randomly by *seller1*, ie.  $w_p = rand(0, 1)$  and  $w_w = 1 - w_p$ . Both *seller1* and *buyer2* will employ the NDF negotiation model to generate their counter-offers, and *buyer1* will employ the proposed geometric method to generate its counter-offers. The NDF negotiation approach is explained briefly as follows.

In the NDF negotiation approach, an agent's response in each negotiation round is defined as follows [FWJ04a]:

$$A^s(t, p_{\hat{a} \rightarrow a}^t) = \begin{cases} Quit & \text{if } t > \tau^a, \\ Accept & \text{if } U^a(p_{\hat{a} \rightarrow a}^t) \geq U^a(p_{a \rightarrow \hat{a}}^{t'}), \\ Offer p_{a \rightarrow \hat{a}}^{t'} \text{ at } t' & \text{otherwise.} \end{cases} \quad (4.18)$$

where  $\tau^a$  is Agent  $a$ 's deadline,  $p_{a \rightarrow \hat{a}}^{t'}$  is the counter-offer from Agent  $a$  to Opponent  $\hat{a}$  at round  $t'$ , and  $U^a(p_{\hat{a} \rightarrow a}^t)$  indicates Agent  $a$ 's utility on the given offer  $p_{\hat{a} \rightarrow a}^t$  from Opponent  $\hat{a}$  at round  $t$ . Agent  $a$ 's counter-offer  $p_{a \rightarrow \hat{a}}^{t'}$  and evaluation function  $U^a(p_{\hat{a} \rightarrow a}^t)$  are defined as follows.

$$p_{a \rightarrow \hat{a}}^t = RP^a \times \left(\frac{t}{\tau^a}\right)^{\lambda^a} + IP^a \times \left[1 - \left(\frac{t}{\tau^a}\right)^{\lambda^a}\right] \quad (4.19)$$

and,

$$U^a(p_{\hat{a} \rightarrow a}^t) = \frac{p_{\hat{a} \rightarrow a}^t - RP^a}{IP^a - RP^a} \quad (4.20)$$

where  $IP^a$  indicates Agent  $a$ 's initial offer,  $RP^a$  indicates Agent  $a$ 's reservation offer, and  $\lambda^a$  indicates Agent  $a$ 's negotiation strategy. For more detail about the NDF negotiation model, please refer to references [FSJ98, LSG05].

### 4.5.2 Experimental Results

By repeating the experiments 1000 times, (parameters being selected randomly from the domains displayed in Table 4.2), we summarize the experimental results from Figures 4.5 through 4.8 to illustrate the improvement by adopting the proposed geometric optimization method. The  $x$ -axis indicates the probabilities that the seller agent may modify its preference in each negotiation round, namely PMP, and the  $y$ -axis indicates the ratio between the negotiation outcomes by using the proposed method and the NDF approach. In Figure 4.5, it can be seen that when the value of PMP shifts from 0% to 100%, *buyer1*'s increment on utility decreases from 13% to 3%. This experimental result indicates that the more likely that an opponent is to modify its preference during a negotiation, the more difficult for an agent to find the optimal offer to increase the agent's utility. That is because when an opponent frequently modifies its preference, it will be more difficult for the agent to accurately estimate the opponent's preference, so the effectiveness of the optimal offer will be decreased. However, in reality, an opponent may not modify its preference very frequently during a negotiation, so the increment on utility in real-world cases will be greater than 9% in general.

In Figure 4.6, the seller's utilities by negotiating with different buyers are also compared. It can be seen that by negotiating with *buyer1*, *seller1*'s utility is improved by at least 20% compared with the negotiation outcome with *buyer2*. The reason behind such a performance is because *seller1* can decide whether an optimal offer from *buyer1* will be accepted based on its own benefit. For example, if *buyer1* wrongly estimates *seller1*'s preference at a certain negotiation round, and generates an incorrect optimal offer, then *seller1* can reject this offer, and reply with a counter-offer. However, *buyer1* will not always wrongly estimate *seller1*'s preference and generate an incorrect optimal offer. If *buyer1*'s estimation is correct at a certain round, then *seller1* will accept the optimal offer, so that *seller1*'s utility is improved similarly for all PMPs.

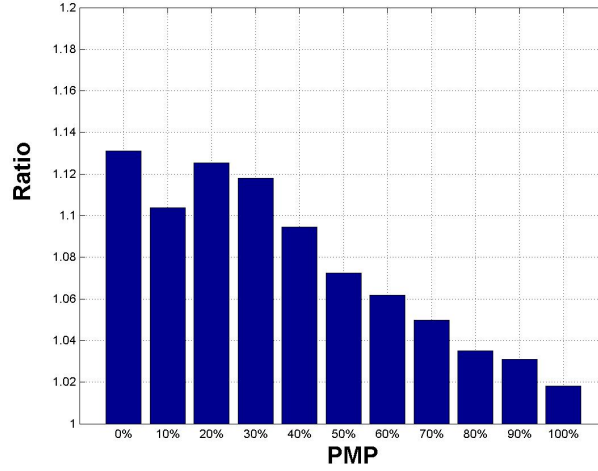
Figure 4.5: The ratio of *buyer1*'s utility to *buyer2*'s utility.

Table 4.3: Negotiation parameters for the study case.

Agent Name	Initial Offer		Reserved Offer		Preference	
	Price	Warranty	Price	Warranty	Price	Warranty
<i>Buyer 1 and 2</i>	\$2090.9	5.1y	\$3001.5	3.45y	0.66	0.34
<i>Seller 1</i>	\$3591.96	3.1y	\$2260.88	5.29y	dynamic	dynamic
<i>Buyer 1 and 2</i> <i>Seller 1</i>	Strategy		Deadline		PMP	
	1.77		22		0%	
	1.33		21		30%	

In Figure 4.7, it can be seen that the number of negotiation rounds is decreased by 20% on average when the geometric method is employed. However, as shown in Figure 4.8, the proposed geometric method needs more computational time to find the optimal offers. The computational time spent on the geometric method is 1.8 times as much as the computational time spent on the NDF approach.

Based on the above experimental results, it can be concluded that by adopting the geometric method, all negotiators's utilities can be increased compared with the original offers, and the negotiation round is also decreased. However, the proposed approach needs more computational time to calculate the optimal offer compared with that of the NDF approach.

### 4.5.3 Case Study

In order to show the detail negotiation process, we adopt an example to demonstrate the proposed negotiation approach, which includes the opponent's behavior

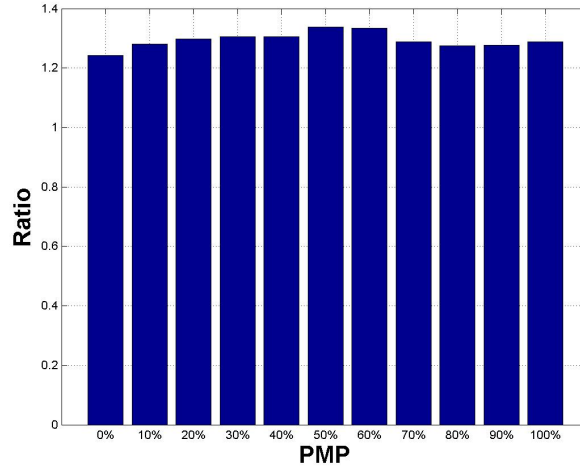


Figure 4.6: The ratio of *seller1*'s utility by negotiating with *buyer1* to *seller1*'s utility by negotiating with *buyer2*.

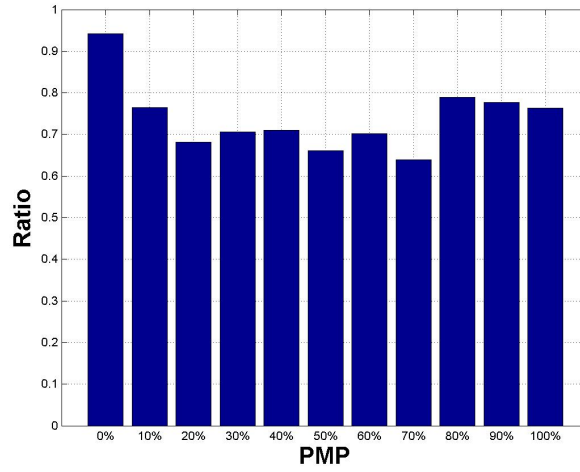


Figure 4.7: The ratio of *buyer1*'s negotiation rounds to *buyer2*'s negotiation rounds.

Table 4.4: *Seller1*'s preference and *buyer1*'s estimation.

Negotiation Round	<i>Seller1</i> 's Preference		<i>Buyer1</i> 's Estimation	
	Price	Warranty	Price	Warranty
1–5	0.886	0.114	0.880	0.120
6	0.988	0.012	0.866	0.134
7	0.499	0.501	0.483	0.517
8–10	0.166	0.834	0.158	0.842
11	0.320	0.680	0.300	0.700
12–13	0.176	0.824	0.167	0.833

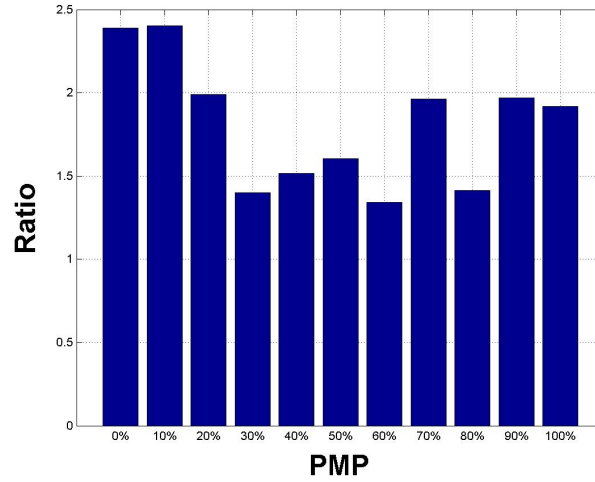


Figure 4.8: The ratio of *buyer1*'s negotiation time to *buyer2*'s negotiation time.

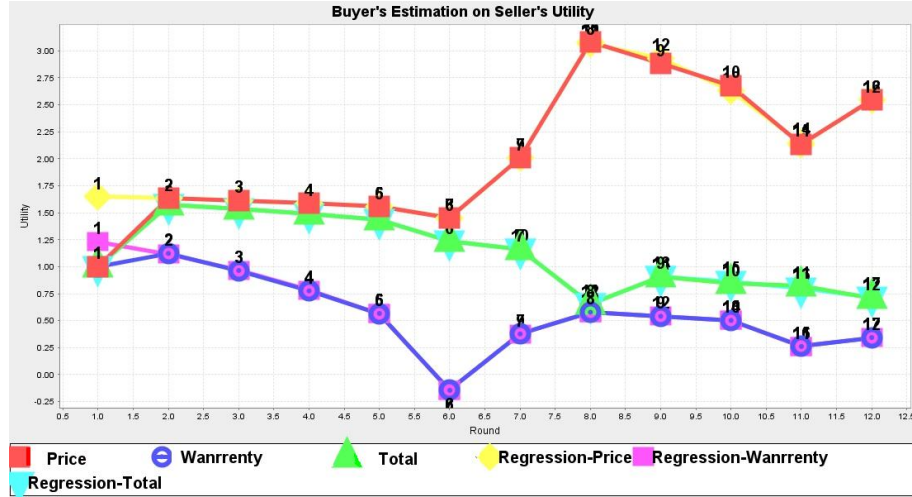


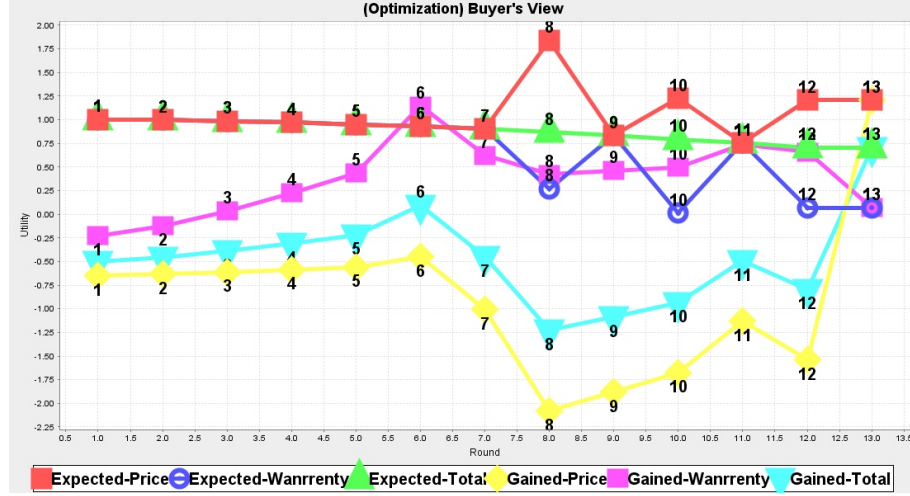
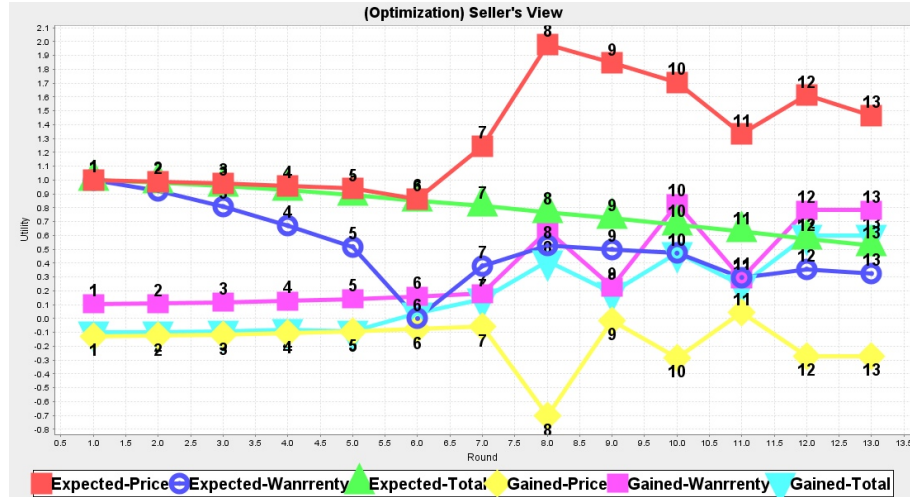
Figure 4.9: *Buyer1*'s estimation on *seller1*'s utility.

prediction, opponent's preference prediction, and optimal offer calculation. All negotiation parameters of this example are listed in Table 4.3. During the negotiation, *seller1* will modify its preference randomly, and the probability of *seller1* modifying its preference in each negotiation round is  $PMP = 30\%$ . Adopting such a PMP, in Table 4.4, *seller1*'s preferences in each negotiation round are listed in the column "Seller's Preference".

Firstly, by adopting the multiple regression method introduced in Section 4.2, *buyer1* can estimate *seller1*'s utility functions for each single issue. The threshold of acceptable error ( $\lambda$ ) for multiple regression is set to 0.05. The regression graph is displayed in Figure 4.9, and all multiple regression functions are listed in Table 4.5.

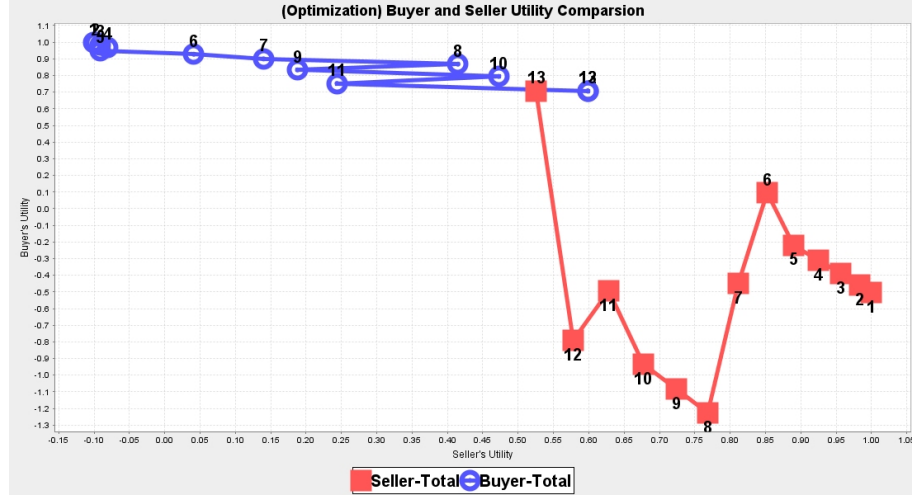
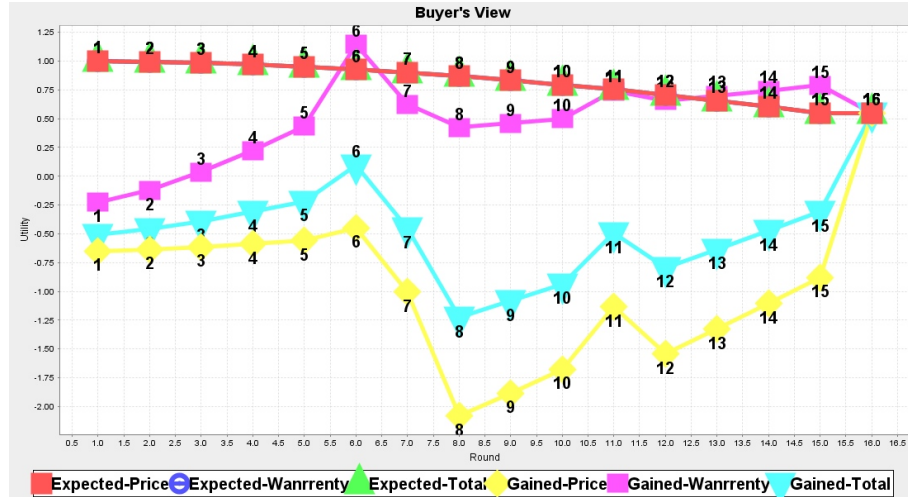
Table 4.5: *Buyer1*'s regression functions on *seller1*'s utility function.

Index	Regression Function	Domain
Regression functions on price		
1	$R(t) = -0.002t^2 - 0.013t + 1.649$	[1, 5]
2	$R(t) = -0.11t + 2$	[5, 6]
3	$R(t) = 0.258t^2 - 2.278t + 6.390$	[6, 8]
4	$R(t) = -0.087t^2 + 1.166t - 0.855$	[8, 11]
5	$R(t) = 0.41t - 1.969$	[11, 12]
Regression functions on warranty		
7	$R(t) = -0.017t^2 - 0.097t + 1.23$	[1, 5]
8	$R(t) = -0.712t + 3.414$	[5, 6]
9	$R(t) = -0.161t^2 + 2.288t - 7.572$	[6, 8]
10	$R(t) = -7.893E - 4t^2 - 0.025t + 0.793$	[8, 10]
11	$R(t) = -0.241t + 2.668$	[10, 11]
12	$R(t) = 0.082t - 0.562$	[11, 12]
Regression functions on overall utility		
13	$R(t) = 0.573t + 1$	[1, 2]
14	$R(t) = -0.003t^2 - 0.029t + 1.605$	[2, 5]
15	$R(t) = 0.0673t^2 - 0.81t + 3.602$	[5, 7]
16	$R(t) = -0.512 * t + 4.235$	[7, 8]
17	$R(t) = 0.258t - 1.155$	[8, 9]
18	$R(t) = -0.011t^2 + 0.148t + 0.426$	[9, 12]

Figure 4.10: *Buyer1*'s view of the negotiation.Figure 4.11: *Seller1*'s view when negotiating with *buyer1*.

Secondly, by adopting the proposed preference estimation method introduced in Section 4.3, *buyer1* can estimate *seller1*'s preference in each negotiation round. The estimation results are listed in Table 4.4 in the column "*Buyer1*'s Estimation". It can be seen that the estimated preferences are very close to *seller1*'s real preferences.

Lastly, by adopting the geometric method introduced in Section 4.4, *buyer1* can calculate the optimal offer in each negotiation round (if it is applicable). The detailed negotiation procedure between *buyer1* and *seller1* is displayed in Figures 4.10 through 4.12. In Figure 4.10, it can be seen that in the 8<sup>th</sup>, 10<sup>th</sup> and 12<sup>th</sup> negotiation rounds, *buyer1* modifies its original offers on the car's price and warranty to increase *seller1*'s utility. However, the total utility of *buyer1* is not damaged.

Figure 4.12: Utilities comparison between *buyer1* and *seller1*.Figure 4.13: *Buyer2*'s view of the negotiation.

Contrary to the buyer's view, it can be seen in Figure 4.11 that after *buyer1* modifies its offers on the two issues, *seller1*'s utility is improved considerably. In Figure 4.12, both *buyer1*'s and *seller1*'s utilities in each negotiation round are displayed. Obviously, it can be seen that in the 8<sup>th</sup>, 10<sup>th</sup> and 12<sup>th</sup> rounds, *seller1*'s utility was improved significantly. Finally, when an agreement is achieved in the 13<sup>th</sup> round, *buyer1*'s utility was 0.706, and *seller1*'s utility was 0.599.

In order to show the improvement by adopting the geometric method, we also illustrate the negotiation process between *buyer2* and *seller1* from Figures 4.13 to 4.15. *Buyer2*'s negotiation parameters are exactly the same as *buyer1*'s, and *seller1*'s negotiation parameters are not changed. In Figures 4.13 and 4.14, it can



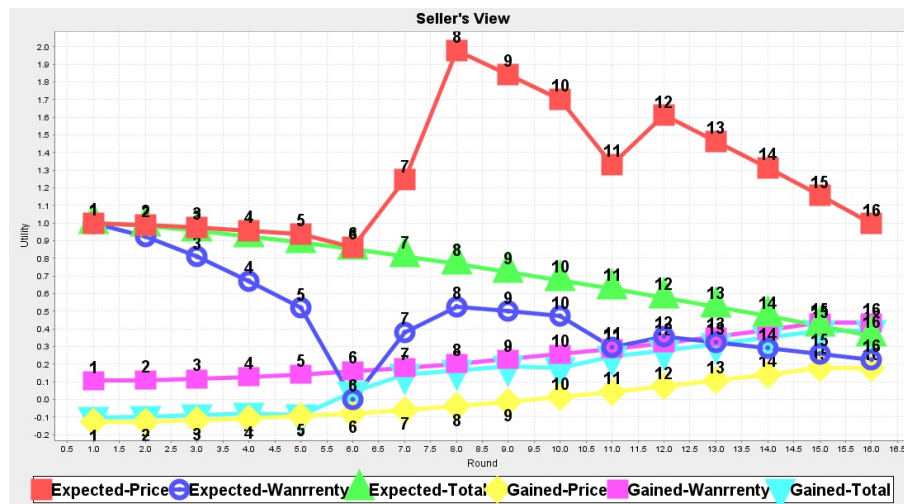


Figure 4.14: *Seller1*'s view when negotiating with *buyer2*.

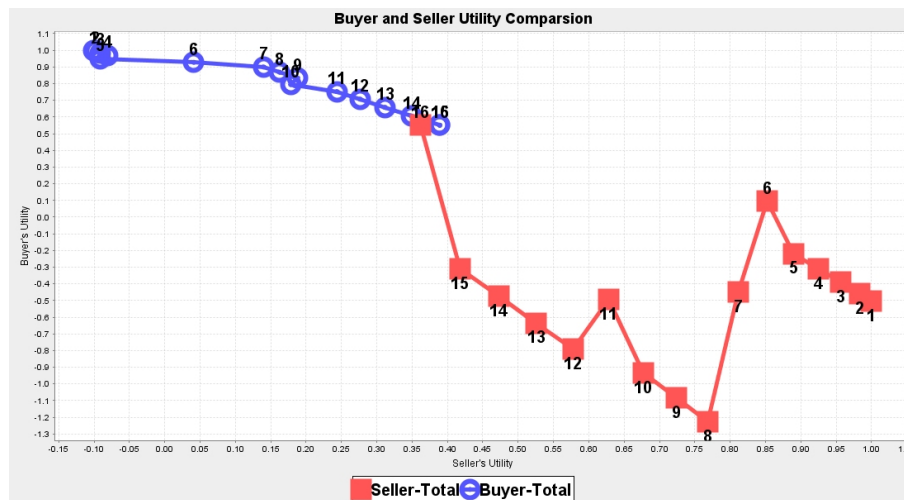


Figure 4.15: Utilities comparison between *buyer2* and *seller1*.

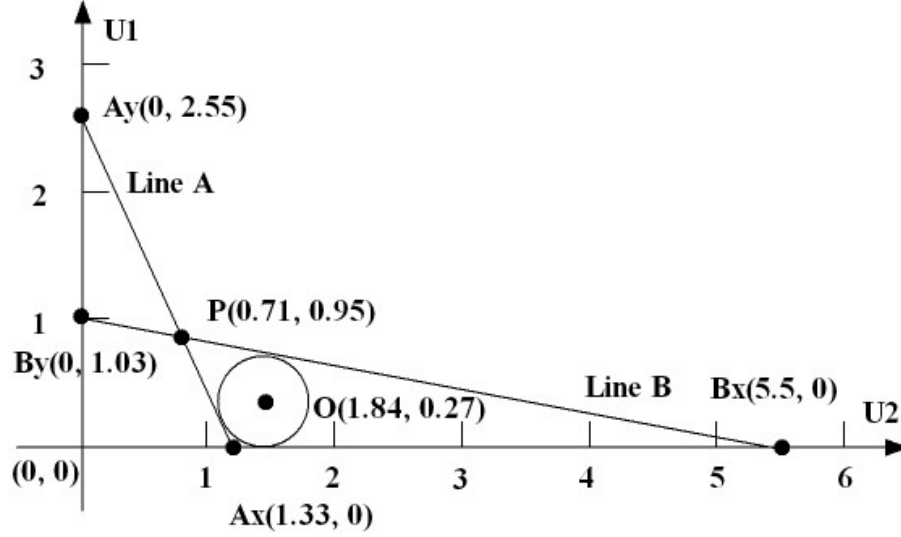


Figure 4.16: *Buyer1*'s optimal offer generation in the 8<sup>th</sup> round.

be seen that *buyer2* only employs the NDF approach to generate counter-offers in each negotiation round, and no negotiator gains any extra benefit during the negotiation. Finally, in Figure 4.15, it can be seen that *buyer2* failed to enlarge its own and *seller1*'s utilities. When agreement is achieved in the 16<sup>th</sup> round, *buyer2*'s utility is 0.551, and *seller1*'s utility is 0.389. By comparing these negotiation outcomes with the outcomes using the geometric method, it can be seen that after adopting the geometric method, the buyer agent's utility is improved by 28%, and the seller agent's utility is improved by 54%. The number of negotiation rounds is also decreased by 19%. However, the computational time spent by the geometric method is around 60% more than the NDF approach.

In detail, for example, in the 7<sup>th</sup> round, when *seller1*'s preference is 0.166 on price and 0.834 on warranty, *seller1* sends an offer (\$4896.99, 4.13year) to both buyers. If *buyer1* or *buyer2* accepts this offer, then *seller1* will get 0.768 utility in total, which is 1.98 on price and 0.527 on warranty. In the 8<sup>th</sup> round, by employing the NDF negotiation approach, *buyer2* rejects *seller1*'s offer, and generates a counter-offer (\$2210.92, 4.84year), which claims 0.868 utility on all issues for itself. If *seller1* accepts this offer, *seller1* will get utilities (−0.038, 0.205), i.e. 0.165 in total. Contrary to *buyer2*, in the 8<sup>th</sup> round, *buyer1* estimates that *seller1*'s preference is (0.158, 0.842), and sends a counter-offer (\$1325.26, 3.89year) as a response. If *seller1* accepts this offer, *buyer1* will get utilities (1.84, 0.27), i.e. 0.868 in total, and *seller1* will get utilities (−0.73, 0.64), i.e. 0.413 in total. Without damaging its

own utility, *buyer1*'s offer increases *seller1*'s utility by 0.248 compared with *buyer2*'s offer. The calculation procedure for *buyer1* at the 8<sup>th</sup> negotiation round by using the geometric method is illustrated in Figure 4.16.

In this section, we illustrated experimental results by applying the proposed geometric method. From both statistical results and the individual case study, we can confidently say that the proposed bilateral optimal multi-issue negotiation approach successfully improves both negotiators' utilities and decreases the numbers of negotiation rounds. However, it needs more computational time to perform sophisticated calculations.

## 4.6 Summary

In this chapter, we proposed an approach for bilateral multi-issue negotiation in open and dynamic environments. Firstly, a multiple regression method is introduced to capture an opponent's negotiation behaviour based only on the opponent's historical offers. Secondly, a preference estimation method is introduced to predict the opponent's preference dynamically during a negotiation. Thirdly, two methods are introduced to find the optimal offer dynamically. The geometric method can illustrate the optimal offer details by a 2D graph directly, but the complexity of the geometric method increases as the number of issues becomes greater than three. By contrast, the algebraic method can easily handle large numbers of issues, but the selection of the constraint value will impact the negotiation result. To sum up, a negotiator should choose a suitable method according to its own specification and requirement in a negotiation. Finally, the geometric method is evaluated by a series of experiments. Both the statistical results and a case study demonstrate improvements of the proposed method on both negotiator's utilities.

# Chapter 5

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## Negotiation Partner Selection

Chapters 3 and 4 proposed two approaches to solve the research problem on the bilateral level, which are agent behavior prediction in bilateral single issue negotiation, and optimization of bilateral multi-issue negotiation. From Chapters 5 to 7, we will turn our attention to the multilateral negotiation level.

### 5.1 Introduction

Traditional negotiation approaches in multi-agent systems (MASs), such as game theory [RC03, LSG05, FSJ98, LLS06, SFJ97] and argumentation-based negotiation [RRJ<sup>+</sup>04, PSJ98, ADM07, nP07], emphasize decision making models to determine the optimal coalition structure and the division of payoff, with a little devotion to the negotiation partners selection. However, when a negotiation contains more participators, it will be inefficient for an agent to perform a sophisticated bargain with each potential partner. If the unqualified partners can be filtered out before a negotiation starts, an agent can pay more concern to partners with a high likelihood of reaching an agreement, so as to improve the efficiency and effectiveness of a negotiation.

In the last decade, researchers have recognized the importance of partner selection in multilateral negotiation and proposed some approaches for selecting suitable partners during the negotiation. In [FSJ98], a significant model was introduced by Faratin et al., which defines a range of strategies and can be employed by computational agents to generate initial offers, evaluate proposals and offer counter proposals. With such a model, in each round of a negotiation, a comprehensive analysis is applied to help agents find the most suitable partners. Kraus [Kra01] further classified negotiations into three categories, which are data allocation, resource allocation and task distribution, according to the application domain of negotiations. In each of

these categories, several complicated and heuristic methods were introduced to help agents find the optimal negotiation agreements under different situations. However, as the rapid development of agents and the Internet techniques, most work environments of MASs become uncertain and dynamic [RSZ07, SC03]. In such open and dynamic environments, when the number of potential partners is huge, to perform complicated negotiations with all of the potential partners may be expensive in terms of computational time and resources, or even impractical. Thus, an appropriate approach which can be employed by agents to choose partners with a high chance of reaching a good agreement in subsequent negotiation from a large number of potential partners is required greatly. Such a selection mechanism is very important because of practicality and efficiency of MASs interactions.

Nevertheless, it is noticed that an agent may perform various behaviors in negotiation by considering its motivation and aim, which makes the partner selection process much more complicated and difficult to steer than expected. Therefore, it is necessary to discuss the kinds of agent behaviors in negotiation before a partner selection mechanism is given. In general, agents may compete or cooperate with each other in order to gain their own goals or a common goal in MASs. The final agreements about how to compete or cooperate are achieved through negotiating. Therefore, negotiations can be classified into *competitive negotiation* and *cooperative negotiation* according to the behaviors of its participants. In a *competitive negotiation*, participators perform the roles as challengers, while in a *cooperative negotiation*, participators are cooperators. Thus, criteria on partner selection are also different in these two kinds of negotiations. For example, in a *cooperative negotiation*, since an agent treats other agents' gains as its own, it will select the agents which can increase global benefits as its partners. In a *competitive negotiation*, an agent prefers to choose a partner which can supply the highest benefit to itself. These two kinds of partner selection strategy are the most simple and direct approaches in extreme situations. Actually, researches [ZLW02, JTK01] found that it is not always beneficial for an agent to only cooperate with others about global tasks in *cooperative negotiation*. Also in a *competitive negotiation*, an agent might need to commit to global tasks for other agents. What is more, in some circumstance, when an agent's behavior is beyond these two extreme situations, an agent cannot adopt these two extreme partner selection approaches simply, because an agent needs both appropriate competition and cooperation to maximize both the local and global utilities.

In order to address above issues mentioned, an extended dual concern model for partner selection in negotiation is proposed in this chapter. Furthermore, based on this model, both linear and non-linear partner selection approaches are proposed. The linear approach employs an agent's preference, and tries to balance the partner selection process between the two extreme situations mentioned above. By contrast, the non-linear approach employs a fuzzy logic mechanism to model and control partner selection process. The advantage of the linear approach is ease of implementation and the generation of results in a short time, while the non-linear approach can handle the situation when an agent's selection criteria cannot be presented linearly. In general, these two approaches have three common merits, which are that: (1) both an agent's own benefit and its partners' benefits are considered; (2) an agent's attitude to its partners is captured; (3) both the linear and non-linear approaches are sensitive to changes in the negotiation environment and can be employed in an open and dynamic negotiation environment.

The remainder of this chapter is organized as follows. In Section 5.2, an extended dual concern model is proposed, the partner selection problem is formally described, and potential partners in a general negotiation are further classified and analyzed. In Section 5.3, a linear approach for the partner selection is proposed. In Section 5.4, a non-linear approach is proposed. In Section 5.5, several examples are demonstrated to evaluate the performance of the proposed partner selection approaches. Finally, Section 5.6 concludes this chapter.

## 5.2 Potential Partners Analysis in General Negotiations

### 5.2.1 The Extended Dual Concern Model

In [ZLW06], Zhang et al. proposed a dual concern model to illustrate the degree of concern between two agents' negotiation outcomes. However, this model just briefly presents the main trend of these degrees, not offering any calculation method about how to decide the values of these degrees and how to compare these degrees. To address these problems, we further extend this dual concern model in order to allow an agent to make reasonable decisions to select partners. The extended dual concern model is shown in Figure 5.1.

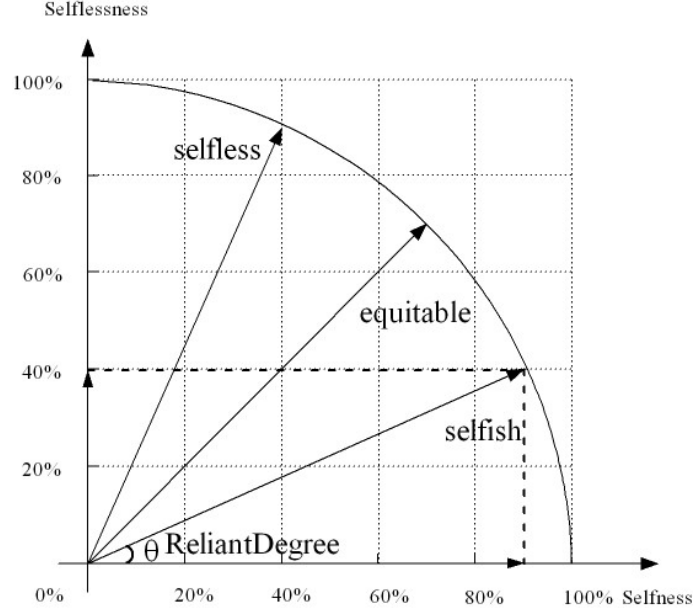


Figure 5.1: The extended dual concern model.

In Figure 5.1, the x-axis indicates the percentage of self-concern of an agent, while the y-axis is the percentage of other-concern from the agent.  $\theta$  presents a *ReliantDegree* (i.e. reflection of the collaboration degree), where  $\theta \in [0^\circ, 90^\circ]$ . We use *selfness* to represent the percentage of self-concern of an agent, which can be calculated by  $\cos(\theta)$ , and *selflessness* to represent the percentage of other-concern, which can be evaluated by  $\sin(\theta)$ . A *ReliantDegree* can illustrate the level of collaboration between the agent and its potential partners. From the extended model, we can find that there are two extreme cases. (1) When the agent only emphasizes on its own benefit, its negotiation attitude is *selfish* ( $\theta = 0^\circ$ ); and (2) When the agent only cares about its partners' benefits, its attitude is *selfless* ( $\theta = 90^\circ$ ).

From this model, it is clear that there are many other cases between *selfish* and *selfless* negotiation behaviors. In subsection 5.2.2, a formal problem description will be given.

### 5.2.2 Problem Description

Suppose that there are  $n$  potential partners for an agent  $ID_x$  in a MAS. If we use a four-tuple  $p_i^x$  to represent the  $i$ th potential partner,  $p_i^x$  can be formally defined as follows:

$$p_i^x = \langle ID_i, GainRatio_i^x, ContributionRatio_i^x, ReliantDegree_i^x \rangle \quad (5.1)$$

where  $ID_i$  is the unique identification of the  $i$ th potential partner, and  $GainRatio_i^x$ ,  $ContributionRatio_i^x$  and  $ReliantDegree_i^x$  are factors used to evaluate the potential partner  $ID_i$ . These three factors are defined in Definitions 5.1 through 5.3, respectively.

**Definition 5.1** *GainRatio $_i^x$  is the ratio between Agent  $ID_x$ 's benefit to the overall benefit of a negotiation, and is defined by Equation 5.2.*

$$GainRatio_i^x = \frac{S}{L} \times 100\% \quad (5.2)$$

where  $GainRatio_i^x \in [0, 100\%]$ ,  $S$  denotes the benefit that agent  $ID_x$  gains by selecting Agent  $ID_i$  as its partners, and  $L$  denotes the overall benefit by completing a task.

**Definition 5.2** *ContributionRatio $_i^x$  is the ratio between Agent  $ID_i$ 's benefit to the overall benefit of a negotiation, and is defined by Equation 5.3.*

$$ContributionRatio_i^x = \frac{I}{L} \times 100\% \quad (5.3)$$

where  $ContributionRatio_i^x \in [0, 100\%]$ ,  $I$  denotes the benefit that Agent  $ID_i$  gains by negotiating with Agent  $ID_x$ , and  $L$  denotes the global benefit by completing a task.

**Definition 5.3** *ReliantDegree $_i^x$  represents Agent  $ID_x$ 's attitude to a negotiation, which includes selfness, selflessness and behaviors between these two extreme cases. ReliantDegree $_i^x$  is defined by Equation 5.4.*

$$ReliantDegree_i^x = \arctan\left(\frac{Cr_x^i}{Cr_i^x}\right) \quad (5.4)$$

where  $ReliantDegree \in [0^\circ, 90^\circ]$ ,  $Cr_x^i$  indicates how Agent  $ID_x$  trusts Agent  $ID_i$ , which can be defined as the trading success ratio between agent  $ID_x$  and  $ID_i$ , or can be assigned by the Agent  $ID_x$  based on the commitment fulfill record of



Agent  $ID_i$ .  $Cr_x^i$  indicates how Agent  $ID_i$  trusts Agent  $ID_x$ , which can be defined in a similar way as  $Cr_x^i$ .

Then the collaboration degree between Agent  $ID_x$  and its potential partner  $ID_i$  is generated as Equation 5.5

$$CollaborationDegree_i^x = f(ID_x, p_i^x) \quad (5.5)$$

By calculating the collaboration degree between agent  $ID_x$  and all of its potential partners, the collaboration degree set (**CollaborationDegree<sup>x</sup>**) is generated as follows:

$$\mathbf{CollaborationDegree}^x = \{CollaborationDegree_i^x | i \in [1, n]\} \quad (5.6)$$

In general, a *selfless* agent will select agents with a higher *ContributionRatio* value as its partners, while a *selfish* agent will select partners based only on the value of *GainRatio*. However, in most cases, agents will behave between these two extreme situations. An agent needs to consider both its own benefit and its partners' benefits. In order to balance the benefit between an agent and its partners, a linear partner selection approach is proposed in the next section.

### 5.3 Partner Selection by Using a Linear Approach

Based on the proposed extended dual concern model of Figure 5.1, a linear approach to select partners by considering the relationship between negotiation participators is proposed in this section.

In order to cover all potential cases in partner selection, we need to consider not only both *GainRatio* and *ContributionRatio*, but also an agent's concerns on these two criteria. An agent's concerns on *GainRatio* and *ContributionRatio* can be represented linearly by a weight. Let  $w_g$  indicate an agent's concern on *GainRatio*, and  $w_c$  indicate an agent's concern on *ContributionRatio*, then  $w_c + w_g = 1$ . The *CollaborationDegree* between Agent  $ID_x$  and a potential partner, Agent  $ID_i$ , is defined as follows:

$$CollaborationDegree_i^x = GainRatio_i^x \times w_g + ContributionRatio_i^x \times w_c \quad (5.7)$$

The *CollaborationDegree* ( $\in [0, 1]$ ) indicates the likelihood that a potential partner is selected by an agent. The greater the *CollaborationDegree*, the more likely

that the potential partner will be selected by the agent. In general, there are three extreme cases between  $w_c$ 's and  $w_g$ 's values.

- When  $w_g = 0$  and  $w_c = 1$ , *CollaborationDegree* is calculated based only on *ContributionRatio*, ie. Agent  $ID_x$ 's attitude for a negotiation is absolutely *selfless*.
- When  $w_g = 1$  and  $w_c = 0$ , *CollaborationDegree* is calculated based only on *GainRatio*, ie. Agent  $ID_x$ 's attitude for a negotiation is absolutely *selfish*.
- When  $w_g = w_c = 0.5$ , *CollaborationDegree* is calculated based on both *GainRatio* and *ContributionRatio* equally, ie. Agent  $ID_x$ 's attitude for a negotiation is *equitable*.

Generally, an agent's concerns on the *GainRatio* and the *ContributionRatio* are calculated by employing the *ReliantDegree* as displayed in Equation 5.8 and Equation 5.9, respectively.

$$w_g = \cos^2(\text{ReliantDegree}) \quad (5.8)$$

$$w_c = \sin^2(\text{ReliantDegree}) \quad (5.9)$$

These definitions of  $w_g$  and  $w_c$  reflect the relationships between the factor of *ReliantDegree* and an agent's preference successfully. For example, as shown in Figure 5.1,

- when *ReliantDegree* =  $0^\circ$ , it is supposed that Agent  $ID_x$  should perform a selfness behavior and only consider its own benefits. According to Equations 5.7 to 5.9,  $w_g = \cos^2(0^\circ) = 1$ ,  $w_c = \sin^2(0^\circ) = 0$ , and  $\text{CollaborationDegree}_i^x = \text{GainRatio}_i^x$ . So Agent  $ID_x$  selects its partners by considering only the *GainRatio*, which accords with the expectation on Agent  $ID_x$ 's behavior.
- when *ReliantDegree* =  $45^\circ$ , Agent  $ID_x$  should consider both its own and its partners' benefits equally. In this case,  $w_g = \cos^2(45^\circ) = 0.5$ ,  $w_c = \sin^2(45^\circ) = 0.5$ , and  $\text{CollaborationDegree}_i^x = \text{GainRatio}_i^x \times 0.5 + \text{ContributionRatio}_i^x \times 0.5$ , so Agent  $ID_x$  considers all negotiators' benefits equally during the partner selection process;

- when  $ReliantDegree = 90^\circ$ , it is supposed that Agent  $ID_x$  should perform a selfless behavior, and only consider about its partners' benefits. In this case,  $w_g = \cos^2(90^\circ) = 0$ ,  $w_c = \sin^2(90^\circ) = 1$ , so  $CollaborationDegree_i^x = ContributionRatio_i^x$ , and Agent  $ID_x$  performs selflessly during the partner selection process.

Finally, by combining Equations 5.7 to 5.9, a potential partner is evaluated by considering the factors of  $GainRatio$ ,  $ContributionRatio$  and  $ReliantDegree$ . Agent  $ID_x$ 's evaluation result on a potential partner  $ID_i$  is defined as follows:

$$CollaborationDegree_i^x = GainRatio_i^x \times \cos^2(ReliantDegree_i^x) + ContributionRatio_i^x \times \sin^2(ReliantDegree_i^x) \quad (5.10)$$

Then by calculating each collaboration degree between Agent  $ID_x$  and its potential partners, the collaboration degrees set (**CollaborationDegree<sup>x</sup>**) are generated, which is:

$$\mathbf{CollaborationDegree^x} = \{CollaborationDegree_i^x | i \in [1, n]\} \quad (5.11)$$

Finally, a sorting algorithm can be employed to select favorable partners or to exclude unqualified partners from the set **CollaborationDegree<sup>x</sup>**.

By employing the proposed approach, the relationships between an agent and its potential partners can be captured. The advantage of this linear approach is easily implemented. However, when an agent's concerns between the factors of  $GainRatio$  and  $ContributionRatio$  cannot be represented linearly, such a linear approach cannot handle the partner selection process anymore. In order to solve such a problem, we will introduce a non-linear partner selection approach in the next section, which employs Fuzzy Logic to capture an agent's opinion during the partner selection process.

## 5.4 Partner Selection by Using a Non-Linear Approach

In some cases, an agent's preference cannot be modeled by a linear function simply. So in order to solve this problem and generate more reasonable selection results,

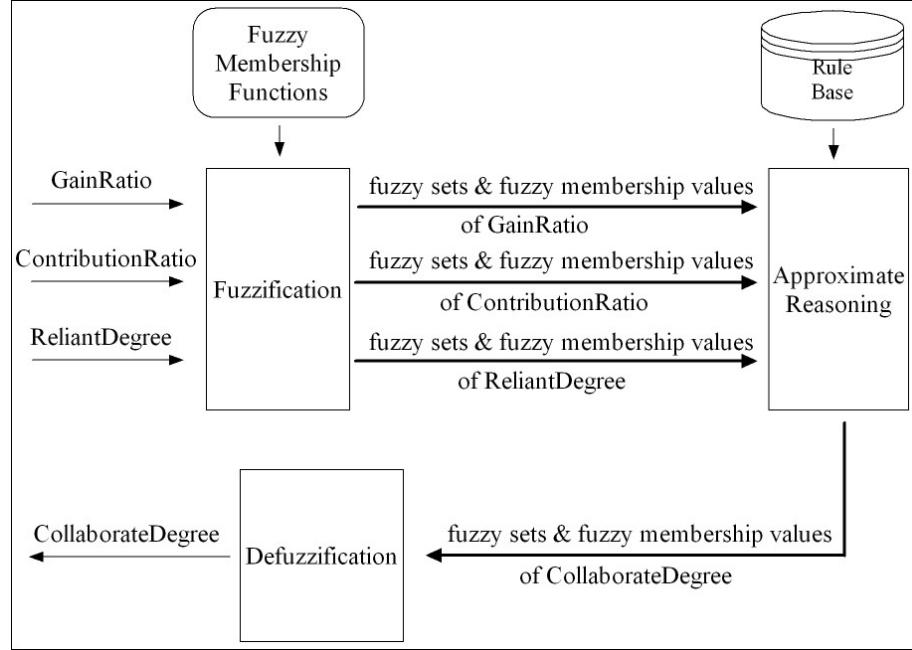


Figure 5.2: The framework of the non-linear partner selection approach.

we propose a non-linear approach for partner selection by employing a Fuzzy Logic [YRP94, KY95] mechanism. The structure of this section is organized as follows. In Subsection 5.4.1, the principle of the proposed non-linear approach and a framework are introduced. In Subsections 5.4.2 through 5.4.4, the methods of fuzzification, approximate reasoning, and defuzzification are introduced in detail, respectively.

### 5.4.1 Framework of a Fuzzy-Based Approach

We assume that an agent can select its suitable partners dynamically by considering its own and its partners' benefits.

The framework of the non-linear approach is graphically illustrated in Figure 5.2. There are five units in this approach, which are: (1) a library of fuzzy functions, (2) a fuzzy rule base, (3) a fuzzification module, (4) an approximate reasoning module, and (5) a defuzzification module.

The input parameters of the framework are *GainRatio*, *ContributionRatio* and *ReliantRatio* which have been defined in Section 5.2. The output of this framework provides suggestions to an agent for partner selection by considering these three factors.

### 5.4.2 Fuzzification

#### Fuzzy Membership Functions for Input Parameters:

The linguistic states of the three input parameters (*GainRatio*, *ContributionRatio* and *ReliantDegree*) are defined as follows.

- ***GainRatio***

For the input parameter *GainRatio*, five linguistic states are selected and expressed by appropriate fuzzy sets, which are {*VerySmall*, *Small*, *Medium*, *Large*, *VeryLarge*}.

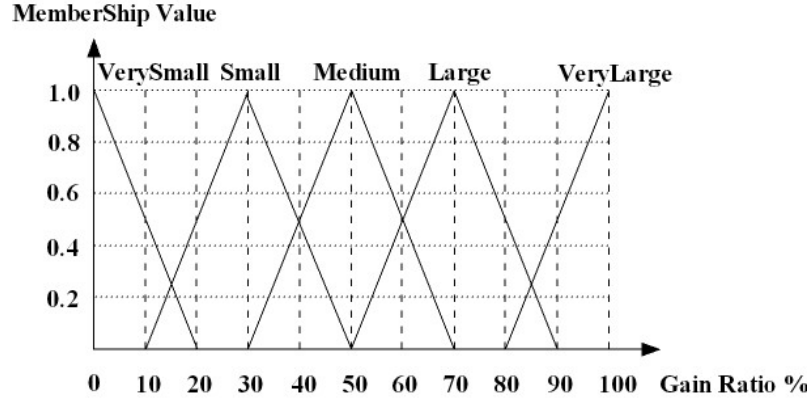
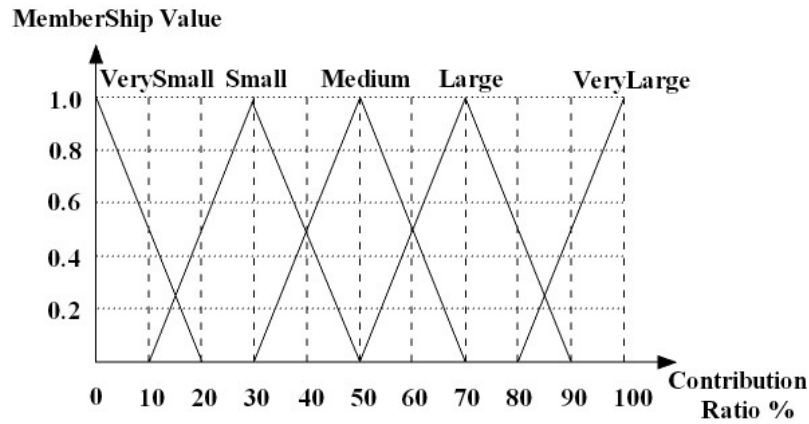
Figure 5.3 depicts these fuzzy sets as applied to the parameter *GainRatio*. The triangular membership function [ESD96] is adopted here to define fuzzy memberships. Fuzzy membership functions for fuzzy sets {*VerySmall*, *Small*, *Medium*, *Large*, *VeryLarge*} are defined in Equations 5.12 through 5.16, respectively.

$$F_{VerySmall}(x) = \begin{cases} \frac{20-x}{20} & 0 \leq x \leq 20 \\ 0 & x > 20 \end{cases} \quad (5.12)$$

$$F_{Small}(x) = \begin{cases} 0 & x \leq 10 \\ \frac{x-10}{20} & 10 < x \leq 30 \\ \frac{50-x}{20} & 30 < x \leq 50 \\ 0 & x > 50 \end{cases} \quad (5.13)$$

$$F_{Medium}(x) = \begin{cases} 0 & x \leq 30 \\ \frac{x-30}{20} & 30 < x \leq 50 \\ \frac{70-x}{20} & 50 < x \leq 70 \\ 0 & x > 70 \end{cases} \quad (5.14)$$

$$F_{Large}(x) = \begin{cases} 0 & x \leq 50 \\ \frac{x-50}{20} & 50 < x \leq 70 \\ \frac{90-x}{20} & 70 < x \leq 90 \\ 0 & x > 90 \end{cases} \quad (5.15)$$

Figure 5.3: Fuzzy quantization of the range  $[0, 100]$  for *GainRatio*.Figure 5.4: Fuzzy quantization of the range  $[0, 100]$  for *ContributionRatio*.

$$F_{VeryLarge}(x) = \begin{cases} 0 & x \leq 80 \\ \frac{x-80}{20} & x > 80 \end{cases} \quad (5.16)$$

where  $x \in [0, 100]$

- ***ContributionRatio***

For the parameter *ContributionRatio*, both the fuzzy sets and membership functions are the same as *GainRatio*'s (Equations 5.12 to 5.16). Figure 5.4 depicts the fuzzy sets as applied to the parameter *ContributionRatio*.

- ***ReliantDegree***

For the parameter *ReliantDegree*, five linguistic states are selected and expressed by appropriate fuzzy sets, which are  $\{Complete\ Self-Driven, Self-Driven, Equitable, External-Driven, Complete\ External-Driven\}$ . Figure 5.5

depicts these fuzzy sets as applied to the parameter *ReliantDegree*. Fuzzy membership functions for fuzzy sets  $\{Complete\ Self-Driven, Self-Driven, Equitable, External-Driven, Complete\ External-Driven\}$  are defined in Equations 5.17 through 5.21, respectively.

$$F_{CompleteSelfDriven}(x) = \begin{cases} \frac{22.5-x}{22.5} & 0 \leq x \leq 22.5 \\ 0 & x > 22.5 \end{cases} \quad (5.17)$$

$$F_{SelfDriven}(x) = \begin{cases} \frac{x}{22.5} & 0 < x \leq 22.5 \\ \frac{45-x}{22.5} & 22.5 < x \leq 45 \\ 0 & x > 45 \end{cases} \quad (5.18)$$

$$F_{Equitable}(x) = \begin{cases} 0 & x \leq 22.5 \\ \frac{x-22.5}{22.5} & 22.5 < x \leq 45 \\ \frac{67.5-x}{22.5} & 45 < x \leq 67.5 \\ 0 & x > 67.5 \end{cases} \quad (5.19)$$

$$F_{ExternalDriven}(x) = \begin{cases} 0 & x \leq 45 \\ \frac{x-45}{22.5} & 45 < x \leq 67.5 \\ \frac{90-x}{22.5} & 67.5 < x \leq 90 \end{cases} \quad (5.20)$$

$$F_{CompleteExternalDriven}(x) = \begin{cases} 0 & x \leq 67.5 \\ \frac{x-67.5}{22.5} & x > 67.5 \end{cases} \quad (5.21)$$

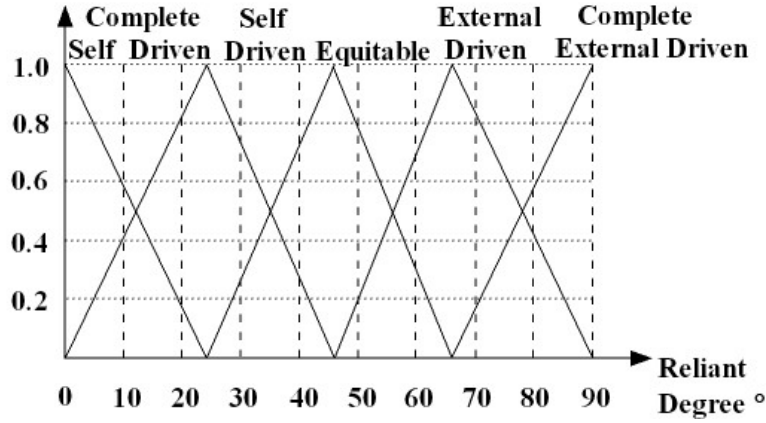
where  $x \in [0^\circ, 90^\circ]$ .

### Fuzzy Membership Functions for Output Parameters:

For the output parameter *CollaborationDegree*, five linguistic states are selected and expressed by corresponding fuzzy sets  $\{Averse, Reluctant, Indifferent, Acceptable, Anticipant\}$ . Figure 5.6 depicts these fuzzy sets as applied to the parameter *CollaborationDegree*. The fuzzy membership functions for the parameter *CollaborationDegree* are defined in Equations 5.22 through 5.26.

$$F_{Averse}(x) = \begin{cases} \frac{20-x}{20} & 0 \leq x \leq 20 \\ 0 & x > 20 \end{cases} \quad (5.22)$$

Membership Value

Figure 5.5: Fuzzy quantization of the range  $[0^\circ, 90^\circ]$  for *ReliantDegree*.

$$F_{Reluctant}(x) = \begin{cases} 0 & x \leq 10 \\ \frac{x-10}{20} & 10 < x \leq 30 \\ \frac{50-x}{20} & 30 < x \leq 50 \\ 0 & x > 50 \end{cases} \quad (5.23)$$

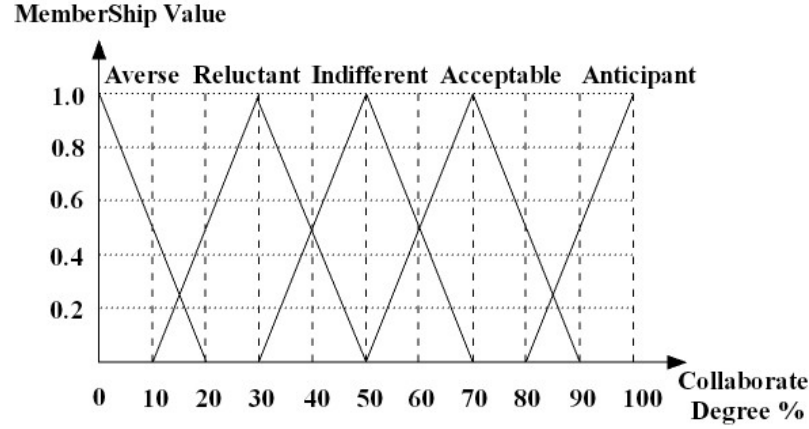
$$F_{Indifferent}(x) = \begin{cases} 0 & x \leq 30 \\ \frac{x-30}{20} & 30 < x \leq 50 \\ \frac{70-x}{20} & 50 < x \leq 70 \\ 0 & x > 70 \end{cases} \quad (5.24)$$

$$F_{Acceptable}(x) = \begin{cases} 0 & x \leq 50 \\ \frac{x-50}{20} & 50 < x \leq 70 \\ \frac{90-x}{20} & 70 < x \leq 90 \\ 0 & x > 90 \end{cases} \quad (5.25)$$

$$F_{Anticipant}(x) = \begin{cases} 0 & x \leq 80 \\ \frac{x-80}{20} & x > 80 \end{cases} \quad (5.26)$$

where  $x \in [0, 100]$



Figure 5.6: Fuzzy quantization of range  $[0, 100]$  for *CollaborationDegree*.

<i>GainRetio</i>	<i>ContributionRetio</i>	<i>CollaborationDegree</i>
<i>VerySmall</i>	Any	<i>Averse</i>
<i>Small</i>	Any	<i>Reluctant</i>
<i>Medium</i>	Any	<i>Indifferent</i>
<i>Large</i>	Any	<i>Acceptable</i>
<i>VeryLarge</i>	Any	<i>Anticipant</i>

Table 5.1: Fuzzy rule base (*ReliantDegree*=*Complete Self-Driven*).

### 5.4.3 Approximate Reasoning

Approximate reasoning is employed to calculate output membership values, which can be further used to compute corresponding output values. The approximate reasoning is based on the use of rules in the rule base.

#### Rule Base:

A rule base is a matrix of combinations of the input linguistic parameters. The rule bases in this approach are displayed in Tables 5.1 through 5.5.

#### The Determination of Output Membership Values:

Each entry of the rule base is a rule, which is defined by *AND*ing three linguistic input parameters to produce an individual output, in the form of:

$$\begin{aligned}
 &\text{IF}((F(\textit{GainRatio}) = \alpha) \text{AND} (F(\textit{ContributionRatio}) = \beta) \\
 &\quad \text{AND} (F(\textit{ReliantDegree}) = \gamma)) \\
 &\quad \text{THEN} F(\textit{CollaborationDegree}) = \delta
 \end{aligned} \tag{5.27}$$

<i>GainRetio</i>	<i>ContributionRetio</i>	<i>CollaborationDegree</i>
<i>VerySmall</i>	<i>VeryLarge</i>	<i>Reluctant</i>
	<i>Others</i>	<i>Averse</i>
<i>Small</i>	<i>VeryLarge</i>	<i>Indifferent</i>
	<i>Others</i>	<i>Reluctant</i>
<i>Medium</i>	<i>VeryLarge</i>	<i>Acceptable</i>
	<i>Large</i>	<i>Acceptable</i>
	<i>Others</i>	<i>Indifferent</i>
<i>Large</i>	<i>VerySmall</i>	<i>Indifferent</i>
	<i>Others</i>	<i>Acceptable</i>
<i>VeryLarge</i>	<i>VerySmall</i>	<i>Acceptable</i>
	<i>Others</i>	<i>Anticipant</i>

Table 5.2: Fuzzy rule base (*ReliantDegree=Self-Driven*).

<i>GainRetio</i>	<i>ContributionRetio</i>	<i>CollaborationDegree</i>
<i>VerySmall</i>	<i>VeryLarge</i>	<i>Indifferent</i>
	<i>Large</i>	<i>Reluctant</i>
	<i>Medium</i>	<i>Averse</i>
	<i>Small</i>	<i>Averse</i>
	<i>VerySmall</i>	<i>Averse</i>
<i>Small</i>	<i>VeryLarge</i>	<i>Acceptable</i>
	<i>Large</i>	<i>Indifferent</i>
	<i>Medium</i>	<i>Reluctant</i>
	<i>Small</i>	<i>Averse</i>
	<i>VerySmall</i>	<i>Averse</i>
<i>Medium</i>	<i>VeryLarge</i>	<i>Anticipant</i>
	<i>Large</i>	<i>Acceptable</i>
	<i>Medium</i>	<i>Indifferent</i>
	<i>Small</i>	<i>Reluctant</i>
	<i>VerySmall</i>	<i>Averse</i>
<i>Large</i>	<i>VerySmall</i>	<i>Anticipant</i>
	<i>Large</i>	<i>Anticipant</i>
	<i>Medium</i>	<i>Acceptable</i>
	<i>Small</i>	<i>Indifferent</i>
	<i>VerySmall</i>	<i>Reluctant</i>
<i>VeryLarge</i>	<i>VerySmall</i>	<i>Anticipant</i>
	<i>Large</i>	<i>Anticipant</i>
	<i>Medium</i>	<i>Anticipant</i>
	<i>Small</i>	<i>Acceptable</i>
	<i>VerySmall</i>	<i>Indifferent</i>

Table 5.3: Fuzzy rule base (*ReliantDegree=Equitable*).

<i>ContributionRatio</i>	<i>GainRatio</i>	<i>CollaborationDegree</i>
<i>VerySmall</i>	<i>VeryLarge</i>	<i>Reluctant</i>
	<i>Others</i>	<i>Averse</i>
<i>Small</i>	<i>VeryLarge</i>	<i>Indifferent</i>
	<i>Others</i>	<i>Reluctant</i>
<i>Medium</i>	<i>VeryLarge</i>	<i>Acceptable</i>
	<i>Large</i>	<i>Acceptable</i>
	<i>Others</i>	<i>Indifferent</i>
<i>Large</i>	<i>VerySmall</i>	<i>Indifferent</i>
	<i>Others</i>	<i>Acceptable</i>
<i>VeryLarge</i>	<i>VerySmall</i>	<i>Acceptable</i>
	<i>Others</i>	<i>Anticipant</i>

Table 5.4: Fuzzy rule base (*ReliantDegree*=*External-Driven*).

<i>ContributionRatio</i>	<i>GainRatio</i>	<i>CollaborationDegree</i>
<i>VerySmall</i>	<i>Any</i>	<i>Averse</i>
<i>Small</i>	<i>Any</i>	<i>Reluctant</i>
<i>Medium</i>	<i>Any</i>	<i>Indifferent</i>
<i>Large</i>	<i>Any</i>	<i>Acceptable</i>
<i>VeryLarge</i>	<i>Any</i>	<i>Anticipant</i>

Table 5.5: Fuzzy rule base (*ReliantDegree*=*Complete External-Driven*).

where  $\alpha \in \{\text{VerySmall}, \text{Small}, \text{Medium}, \text{Large}, \text{VeryLarge}\}$ ,  $\beta \in \{\text{VerySmall}, \text{Small}, \text{Medium}, \text{Large}, \text{VeryLarge}\}$ ,  $\gamma \in \{\text{Complete Self-Driven}, \text{Self-Driven}, \text{Equitable}, \text{External-Driven}, \text{Complete External-Driven}\}$ ,  $\delta \in \{\text{Averse}, \text{Reluctant}, \text{Indifferent}, \text{Acceptable}, \text{Anticipant}\}$ , and  $F(\text{CollaborationDegree})$  denotes a fuzzy set into which the parameter *CollaborationDegree* is mapped.

An output membership value  $\mu_\delta(\nu)$  can be calculated by Equation 5.28.

$$\mu_\delta(\nu) = \min(\mu_\alpha(\text{GainRatio}), \mu_\beta(\text{ContributionRatio}), \mu_\gamma(\text{ReliantDegree})) \quad (5.28)$$

#### 5.4.4 Defuzzification

There are many defuzzification approaches. The centroid defuzzification method [ESD96] is used to defuzzify the output membership values.

$$DV = \frac{\sum_{i=1}^k (\nu_i \times \mu(\nu_i))}{\sum_{i=1}^k \mu(\nu_i)} \quad (5.29)$$

Partner	<i>GainRatio</i>	<i>ContributionRatio</i>	<i>ReliantDegree</i>
$g_a$	80%	20%	0°
$g_b$	50%	50%	0°
$g_c$	20%	80%	0°

Table 5.6: Input parameters for Scenario 1.

where  $\mu(\nu_i)$  is the  $i$ th output membership value,  $\nu_i$  is its corresponding output value, and  $k$  is the number of fuzzy rules which are activated.

$DV$  is the final output value of *CollaborationDegree* in a particular case.  $DV$  can be used to evaluate the relationship between the agent and its potential partners, and can also be used as an important factor for selecting or adopting a most suitable partner for an agent in a particular case.

In this section, we proposed a non-linear approach for the partner selection. By comparison with the linear approach introduced in Section 5.3, the non-linear approach is more logical and accurate. However, it needs a more complex process to achieve the selection results.

## 5.5 Case Study

In this session, four scenarios are demonstrated. In each Scenario, Agent  $g$  is going to select the most suitable partner from three potential partners (Agents  $g_a$ ,  $g_b$  and  $g_c$ ). These scenarios illustrate how both our linear and non-linear approaches select the most suitable partner for Agent  $g$ .

### 5.5.1 Scenario 1

In Scenario 1, all three potential partners share a common *ReliantDegree*, which is 0°. Agent  $g$  is a *Complete Self-Driven* agent so that Agent  $g_a$  should be selected as the most suitable partner because it can contribute the highest *GainRatio* to Agent  $g$  among three potential partners. All input parameters for the three potential partners are shown in Table 5.8

In Table 5.7, the selection results by using the proposed linear function are presented. Since  $w_g = \cos^2(0^\circ) = 1$  and  $w_c = \sin^2(0^\circ) = 0$ , the *GainRatio* is used to make the final decision. Therefore, Agent  $g_a$  is selected by Agent  $g$  as the most preferable partner, which is the same as the estimation.

Partner	$w_g \times GainRatio$	$w_c \times ContributionRatio$	$CollaborationDegree$
$g_a$	0.8	0	0.8
$g_b$	0.5	0	0.5
$g_c$	0.2	0	0.2

Table 5.7: Output for Scenario 1 by using the linear function.

Partner	<i>ReliantDegree</i>	<i>GainRatio</i>	<i>ContributionRatio</i>	<i>CollaborationDegree</i>	Defuzzification
$g_a$	<i>Complete</i> <i>Self-Driven</i> =1	<i>Large</i> =0.5	<i>Small</i> =0.5	<i>Acceptable</i> =0.5	70%
$g_b$	<i>Complete</i> <i>Self-Driven</i> =1	<i>Medium</i> =1	<i>Medium</i> =1	<i>Indifferent</i> =1	50%
$g_c$	<i>Self-Driven</i> =1	<i>Small</i> =0.5	<i>Large</i> =0.5	<i>Reluctant</i> =0.5	30%

Table 5.8: Output for Scenario 1 by using the non-linear function.

The results for Scenario 1 by using the proposed non-linear function are shown in Table 5.8. According to the selection results generated by the proposed approach, Agent  $g_a$  is the most suitable partner, which is the same as the selection result generated by the linear approach.

### 5.5.2 Scenario 2

In Scenario 2, all three potential partners share a common *ReliantDegree*, which is  $90^\circ$ . Both the *GainRatio* and *ContributionRatio* are the same as Scenario 1. Agent  $g$  is a *Complete External-Driven* agent so that Agent  $g_c$  should be selected as the most suitable partner because it has the largest *ContributionRatio*. All input parameters for the three potential partners are shown in Table 5.9.

Since *ReliantDegree* is  $90^\circ$ ,  $w_g = 0$  and  $w_c = 1$  according to Equations 5.8 and 5.9. Agent  $g$  selects a partner based on *ContributionRatio* only. The selection results by using the linear function are displayed in Table 5.10. According to these results, Agent  $g_c$  should be selected as the most suitable partner for Agent  $g$ . This selection result is exactly the same as the output generated by using the non-linear function as shown in Table 5.11.

Partner	<i>GainRatio</i>	<i>ContributionRatio</i>	<i>ReliantDegree</i>
$g_a$	80%	20%	$90^\circ$
$g_b$	50%	50%	$90^\circ$
$g_c$	20%	80%	$90^\circ$

Table 5.9: Input parameters for Scenario 2.

Partner	$w_g \times GainRatio$	$w_c \times ContributionRatio$	$CollaborationDegree$
$g_a$	0	0.2	0.2
$g_b$	0	0.5	0.5
$g_c$	0	0.8	0.8

Table 5.10: Output for Scenario 2 by using the linear function.

Partner	<i>ReliantDegree</i>	<i>ContributionRatio</i>	<i>GainRatio</i>	<i>CollaborationDegree</i>	Defuzzification
	<i>Complete</i>				
$g_a$	<i>External-Driven</i> =1	<i>Small</i> =0.5	<i>Large</i> =0.5	<i>Reluctant</i> =0.5	30%
$g_b$	<i>External-Driven</i> =1	<i>Medium</i> =1	<i>Medium</i> =1	<i>Indifferent</i> =1	50%
$g_c$	<i>Self-Driven</i> =1	<i>Large</i> =0.5	<i>Small</i> =0.5	<i>Acceptable</i> =0.5	70%

Table 5.11: Output for Scenario 2 by using the non-linear function.

### 5.5.3 Scenario 3

In Scenario 3,  $ReliantDegree = 45^\circ$  and all others parameter are the same as Scenario 1. In this case, Agent  $g$  is an *Equitable* agent so that the estimation partner is any of the potential partners by considering both *GainRatio* and *ContributionRatio* equally. All input parameters for the three potential partners are shown in Table 5.12.

According to the proposed linear function, since  $ReliantDegree = 45^\circ$ , then  $w_g = w_c = 0.5$ . The *CollaborationDegree* for all potential partners is exactly the same (0.5), as shown in Table 5.13. Any partner agent could be selected as the most preferable partner for Agent  $g$ . The non-linear approach selection results are displayed in Table 5.14. It also suggests that any potential partner could be the most suitable partner in this case.

### 5.5.4 Scenario 4

In Scenario 4, all three potential partners share a common *GainRatio* and *ContributionRatio*, but have a different *ReliantDegree*. Agent  $g$  has different attitudes to its potential partners. For potential partner  $g_a$ , Agent  $g$  performs as a *Complete Self-Driven* agent so that only the *GainRatio* (80%) will be used to select the most suitable partner. For potential partner  $g_b$ , Agent  $g$  performs as an *Equitable* agent,

Partner	<i>GainRatio</i>	<i>ContributionRatio</i>	<i>ReliantDegree</i>
$g_a$	80%	20%	$45^\circ$
$g_b$	50%	50%	$45^\circ$
$g_c$	20%	80%	$45^\circ$

Table 5.12: Input parameters for Scenario 3.

Partner	$w_g \times GainRatio$	$w_c \times ContributionRatio$	$CollaborationDegree$
$g_a$	0.4	0.1	0.5
$g_b$	0.25	0.25	0.5
$g_c$	0.1	0.4	0.5

Table 5.13: Output for Scenario 3 by using the linear function.

Partner	<i>ReliantDegree</i>	<i>GainRatio</i>	<i>ContributionRatio</i>	<i>CollaborationDegree</i>	Defuzzification
$g_a$	<i>Equitable</i> =1	<i>Large</i> =0.5	<i>Small</i> =0.5	<i>Indifferent</i> =0.5	50%
$g_b$	<i>Equitable</i> =1	<i>Medium</i> =1	<i>Medium</i> =1	<i>Indifferent</i> =1	50%
$g_c$	<i>Equitable</i> =1	<i>Small</i> =0.5	<i>Large</i> =0.5	<i>Indifferent</i> =0.5	50%

Table 5.14: Output for Scenario 3 by using the non-linear function.

so that both *GainRatio* (80%) and *ContributionRatio* (20%) will be used to evaluate whether  $g_b$  could be chosen as a suitable partner. Therefore, the final benefit of considering both *GainRatio* and *ContributionRatio* for  $g_b$  should be between 20% and 80%. For potential partner  $g_c$ , Agent  $g$  performs as a *Complete External-Driven* agent so that only the benefit of *ContributionRatio* (20%) will be used for the selection of  $g_c$  as a partner. By comparing the three cases, Agent  $g_a$  should be selected as the most suitable partner because Agent  $g$  would gain the largest benefit(80%) when collaborating with Agent  $g_a$ . All input parameters for the three potential partners are shown in Table 5.15

By employing the proposed linear approach, partner  $g_a$  is selected as the most suitable partner shown in Table 5.16. Because these three partners can offer the same *GainRatio* and *ContributionRatio*, the relationships between Agent  $g$  and each of them are crucial for partner selection in this case. As the *GainRatio* is bigger than *ContributionRatio*, and Agent  $g$ 's attitude on partner  $g_a$  is selfness, so  $g_a$  is the preferred partner. In Table 5.17, the selection results by employing the non-linear function are presented, which are the same as the linear approach.

Therefore, from these four different scenarios, it can be seen that by considering the factors of *GainRatio*, *ContributionRatio* and *ReliantDegree* between the agent and its potential partners, both of our proposed partner selection mechanisms can

Agent	<i>GainRatio</i>	<i>ContributionRatio</i>	<i>ReliantDegree</i>
$g_a$	80%	20%	0°
$g_b$	80%	20%	45°
$g_c$	80%	20%	90°

Table 5.15: Input parameters for Scenario 4.

Partner	$w_g \times GainRatio$	$w_c \times ContributionRatio$	$CollaborationDegree$
$g_a$	0.8	0	0.8
$g_b$	0.4	0.1	0.5
$g_c$	0	0.2	0.2

Table 5.16: Output for Scenario 4 by using the linear function.

Agent	$ReliantDegree$	$GainRatio$	$ContributionRatio$	$CollaborationDegree$	Defuzzification
$g_a$	$Self-Driven=1$	$Large=0.5$	$Small=0.5$	$Acceptable=0.5$	70%
$g_b$	$Equitable=1$	$Large=0.5$	$Small=0.5$	$Indifferent=0.5$	50%
$g_c$	$External-Driven=1$	$Small=0.5$	$Large=0.5$	$Reluctant=0.5$	30%

Table 5.17: Output for Scenario 4 by using the non-linear function.

be employed by agents to generate reasonable judgement on their potential partners and to select the most suitable partner for the agent. Also, it is noticed that both of the proposed approaches is easily administrated by agents in a dynamic negotiation environment to filter partners according to agents' expectations. However, the proposed linear and non-linear approaches have their own individual merits. The linear approach is suitable for a negotiation environment where the situation is not complex and the requirement on accuracy is not very high, but where a quick solution is needed for any changes to the situation. Furthers, the non-linear approach can be employed in a more complex negotiation, where agents' behaviors cannot be represented by linear function simply. The non-linear function is sensitive to changes of situation and can generate more reasonable and accurate selection results by employing predefined fuzzy linguistic languages and membership functions. Therefore, the purpose of proposing two partner selection functions is to satisfy most kinds of requirements in different negotiation environments.

## 5.6 Summary

In this chapter, we identified four potential cases of relationships between an agent and its potential partners. Both linear and non-linear partner selection approaches were proposed. For the linear approach, the  $ReliantDegree$  is employed to calculate the normalized weights for both  $GainRatio$  and  $ContributionRatio$ . Agents attitudes on their potential partners are represented and controlled by these two normalized weights. For the non-linear approach, a framework is proposed which consists of a fuzzification module, a fuzzy rule base, an approximate reasoning module, a defuzzification module, and a library of fuzzy membership functions. All of the fuzzy



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membership functions for corresponding fuzzy sets have been carefully defined and rules of fuzzy logic operations during the procedure of approximate reasoning have also been defined.

## Chapter 6

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# Market-Driven Strategy for Multilateral Single Issue Negotiation

## 6.1 Introduction

In Chapter 5, linear and non-linear partner selection approaches were introduced to filter out unqualified partners before a negotiation starts. By employing such a mechanism, an agent can pay more attention to negotiation with partners who have a greater likelihood to reach an agreement. In this chapter, a market-driven negotiation strategy is introduced to handle multilateral single issue negotiation.

Automated negotiation [RZ94] has been an active research area in recent years. Research on agent negotiation [JFL<sup>+</sup>01, LWJ03] has received a great deal of attention in the areas of multi-agent systems and e-commerce [HJL03, GSW04]. Currently, one of the most crucial issues for automated negotiation is how to reach an agreement when the negotiation environment becomes open and dynamic, ie. a negotiation contains more than two negotiators. Although some agent-based systems [RAMN<sup>+</sup>98, CM96, CDGM01, GM99, GM98, WWW98, LJS<sup>+</sup>03] have been proposed and implemented successfully by researchers, agents involved in these systems usually can only adopt predetermined strategies to negotiate with others. Therefore, when a negotiation environment is open and dynamic, such as more products and services becoming available and negotiators either entering or leaving the negotiation dynamically, agents cannot provide reasonable responses to changes in the negotiation environment by adopting their current negotiation strategies straightaway. Furthermore, negotiators may also be bounded by restrictions such as deadlines and resource limitations. Agents may also need to modify their negotiation strategies when the pressure from these restrictions changes. The Market-Driven Agents (MDAs) model [Sim02, SC03, Sim04, RSZ07] is one strategy which takes into account the relationship between an agent's negotiation strategies and a negotiation

environment. Through comparing the MDAs model [Sim04, Sim02, SW01] and other negotiation strategies [RAMN<sup>+</sup>98, CM96, CDGM01, GM99, GM98, WWW98], the efficient performance of the MDAs model has been illustrated. In the MDAs model, agents are guided by four concession factors, and these factors determine how much concession agents can give during the negotiation based on the environment. These concession factors are *trading opportunity* (see Subsection 6.2.2), *trading competition* (see Subsection 6.2.3), *trading time and strategy* (see Subsection 6.2.4) and *eagerness* (see Subsection 6.2.5).

However, even though the MDAs model considers the relationship between an agent's strategies and the negotiation environment, it does not take into account the situation when the negotiation environment becomes open and dynamic. In an open and dynamic environment, agents may enter into and leave off a negotiation freely, and so the uncertainty of the negotiation may increase. In order to have a broad view on the negotiation environment, we adopt Sycara's model [LGS06, LSG05] to classify negotiations according to the complexity of their environment. The model is illustrated in Fig. 6.1, and according to this model, negotiations are divided into three levels. The negotiation which is processed within the simplest environment is named *single-threaded negotiation*. In this level, the negotiation is carried out between only two agents without any outside options. None of the negotiators can leave off the negotiation before an agreement is reached or a deadline is met, and also no agent can enter into the negotiation during the process. The second level is named *synchronized multi-threaded negotiations*, in which the negotiation is processed among multiple agents. Therefore, agents need more complex negotiation strategies in order to reach an agreement when they face more than one negotiator. As with the first level, all negotiators are still not allowed to leave off and enter into the negotiation freely. Therefore, in this level, agents make any decision in the negotiation based on the current negotiation environment only. The third level is named *dynamic multi-threaded negotiations*. In this level, all negotiators can leave and enter the negotiation dynamically. Therefore, agents should think about not only the current situation but also possible changes to the negotiation environment. According to the classification, at the present time, the MDAs model can work well on the first two levels, but cannot handle negotiation on the third level. In order to address this issue, in this chapter, we propose to extend the MDAs model to third level negotiation by considering the uncertain and dynamic outside options.

The rest of this chapter is organized as follows. In Section 6.2, the principle of the

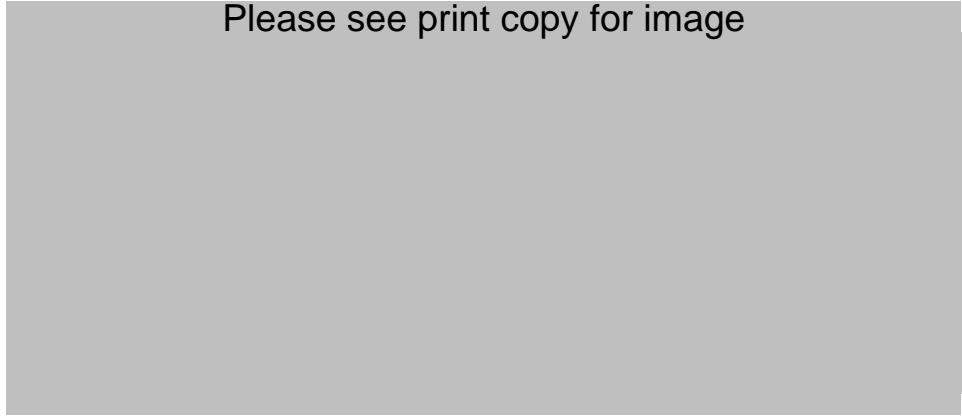


Figure 6.1: A nested view of general negotiation models [LGS06].

MDAs model is introduced briefly. Section 6.3 introduces the proposed mechanisms to extend the MDAs model. Section 6.4 illustrates the experimental results. Section 6.5 concludes this chapter.

## 6.2 A Model for Market-Driven Agents

In this section, the principle of the MDAs model [SC03] is recalled briefly and in particular all four concession factors in MDA are also recaped. Finally, we discuss the limitations of the MDAs model in order to highlight the motivation of this chapter.

### 6.2.1 Principle of the MDAs Model

In order to make reasonable negotiation strategies according to the negotiation environment, agents may need to modify the spread  $k$  that is defined as the difference between an agent's proposal and the counterproposal of its trading partners. For example, if the price of a car is \$10000, and the buyer would only like to pay \$9000, then the spread  $k$  for both seller and buyer is \$1000. In general, when  $k$  is large, the probability that agents may complete the negotiation will be decreased, and conversely when  $k$  is small, the probability will be increased. Therefore, by modifying the spread  $k$ , agents can maintain the benefits gained from their partners and increase the likelihood of completing the negotiation. Let  $k'$  denote the spread in the next negotiation round, then  $k'$  is determined by assessing current negotiation situation as follows:

$$k' = O(n, \omega_i, v)C(m, n)T(t, t', \tau, \lambda)E(\varepsilon)k \quad (6.1)$$

where  $O(n, \omega_i, v)$  is the factor for *trading opportunity* that determines the amount of concession according to an agent's expectation about the negotiation outcome, the number of partners and partners' offers (see Subsection 6.2.2);  $C(m, n)$  is the factor for *trading competition*, which is determined by the probability that an agent is ranked as the most preferred trader by at least one of its partners (see Subsection 6.2.3);  $T(t, t', \tau, \lambda)$  is the factor for *trading time and strategy* that determines an agent's rate on concession by considering time constraints (see Subsection 6.2.4); and  $E(\varepsilon)$  is the factor for *eagerness* that determines the amount of concession by considering an agent's eagerness to finish the negotiation (see Subsection 6.2.5). In the following subsections, each of these concession factors will be discussed in detail, respectively.

### 6.2.2 Trading Opportunity

In MDAs, the following factors are considered in order to determine the trading opportunity:

- the number of partners  $n$ ;
- the spread  $k$  between an agent and its partners; and
- the probability  $p$  of completing a negotiation.

Let  $p$  and  $p'$  represent the probabilities of an agent completing a negotiation in the current and next negotiation round, respectively. Let  $k$  and  $k'$  be values of the current and next spreads, respectively. If the distance between  $p$  and  $p'$  is large, in order to keep a reasonable probability of finishing the negotiation, an agent may increase the distance between  $k$  and  $k'$ . By contrast, if the distance between  $p$  and  $p'$  is small, an agent may decrease the distance between  $k$  and  $k'$  in order to maintain its benefit. The relationship between these four factors is represented as follows:

$$k' = \frac{p}{p'} \times k \quad (6.2)$$

Suppose in a negotiation round, agent  $B_1$ 's last offer is represented as a utility vector  $v = (v_b, v_s)$  and its partner  $S_1$ 's offer as a utility vector  $\omega = (\omega_b, \omega_s)$ .  $B_1$ 's last offer generates a payoff of  $v_b$  for itself and  $v_s$  for  $S_1$ ; and  $S_1$ 's offer generates a

payoff of  $\omega_s$  for itself and  $\omega_b$  for  $B_1$ . Let  $c_b$  denote the worst possible utility (*conflict utility*) for  $B_1$ . If the subjective probability of  $B_1$  obtaining  $c_b$  is  $p_c$ , we have:

$$[(1 - p_c)v_b + p_c c_b] \leq \omega_b \quad (6.3)$$

According to inequality (6.3), the highest conflict probability that  $B_1$  may encounter is the maximum value of  $p_c$  as follows:

$$p_c = \frac{v_b - \omega_b}{v_b - c_b} = \frac{k}{v_b - c_b} \quad (6.4)$$

Consequently, the aggregated conflict probability that  $B_1$  may encounter by considering all partners is:

$$P_c = \prod_{i=1}^n p_i = \prod_{i=1}^n \frac{k_i}{v_b - c_b} = \frac{\prod_{i=1}^n (v_b - \omega_i)}{(v_b - c_b)^n} \quad (6.5)$$

where  $k_i$  is the spread between  $B_1$ 's offer and  $S_i$ 's offer, and  $n$  is the number of  $B_1$ 's partners. Therefore, the probability  $p$  that  $B_1$  will obtain a utility  $v_b$  with at least one partner is:

$$p = 1 - P_c = 1 - \frac{\prod_{i=1}^n (v_b - \omega_i)}{(v_b - c_b)^n} \quad (6.6)$$

From Equation (6.2) and (6.6), we get the relationship between the current and next negotiation round as follows:

$$k' = \frac{1}{p'} \left( 1 - \frac{\prod_{i=1}^n (v_b - \omega_i)}{(v_b - c_b)^n} \right) k \quad (6.7)$$

Then the function to represent the concession factor *trading opportunity* is:

$$O(n, \omega_i, v) = \frac{1}{p'} \left( 1 - \frac{\prod_{i=1}^n (v - \omega_i)}{(v - c)^n} \right) \quad (6.8)$$

### 6.2.3 Trading Competition

The concession factor *trading competition* in the MDAs model is calculated by taking into account the probability that an agent will not be considered as the most preferred partner by its partners. Suppose that Agent  $B_1$  has  $m - 1$  competitors  $B_2, \dots, B_m$  and  $n$  partners  $S_1, \dots, S_n$ . The probability that  $B_1$  is not considered as the most preferred partner by all  $S_i$  is  $(\frac{m-1}{m})^n$ . Hence, the concession factor *trading*

*competition* is defined in Equation (6.9), which indicates the probability that  $B_1$  is considered as the most preferred partner by at least one of  $S_i$ .

$$C(m, n) = 1 - \left(\frac{m-1}{m}\right)^n \quad (6.9)$$

### 6.2.4 Trading Time and Strategy

To enable an agent to change its negotiation strategy during a negotiation to get better outcomes, Fatima et. al. [FWJ04a] designed negotiation strategies such as:

1. To complete the negotiation as quickly as possible, an agent makes large concessions at the early stages of a negotiation, and small concessions when at the later stages of a negotiation;
2. To guarantee their benefits, an agent makes small concessions at the early stages of a negotiation. However, when the deadline is approaching, in order to avoid negotiation failure, agents will make large concessions;
3. To process negotiation in a smooth way, an agent makes constant concessions throughout a negotiation.
4. To act on behalf of some human users who are obstinate, an agent keep its original offers throughout a negotiation without any concession.

In general, the concession strategies mentioned above can be Equationed by considering the time constraints as follows [FWJ04a]:

$$k' = [1 - (t/\tau)^\lambda] \times k_0 \quad (6.10)$$

where  $k_0$  is the initial spread,  $t$  is the current negotiation time,  $\tau$  is the negotiation deadline ( $t \leq \tau$ ) and  $\lambda$  is a nonnegative temporal sensitivity factor that decides agents' negotiating strategies as shown in Figure 6.2.

1. When  $\lambda > 1$ , the rate of change in the slope is increasing, corresponding to smaller concessions in the early stages of a negotiation but large concessions in the later stages.
2. When  $0 < \lambda < 1$ , the rate of change in the slope is decreasing, corresponding to large concessions in the early stages but smaller concessions in the later stages.

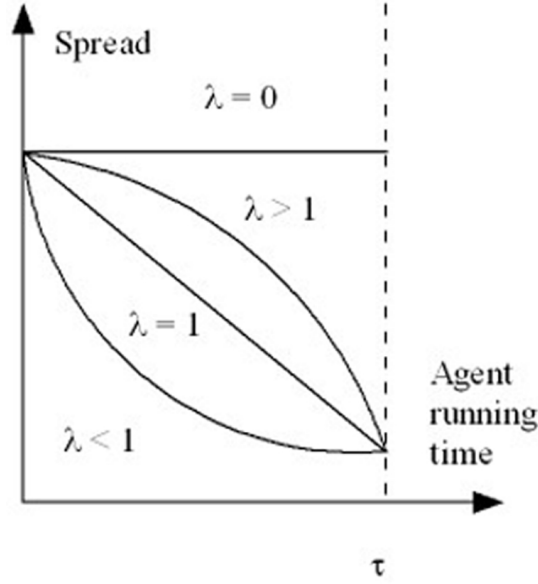


Figure 6.2: Modeling different rates of concession.

3. When  $\lambda = 1$ , the rate of change in the slope is zero, corresponding to making a constant concession throughout a negotiation.
4. When  $\lambda = 0$ , the rate of change of the slope and the slope itself are always zero, corresponding to not making any concession throughout a negotiation.

Let the spread at  $t$  (when the last bid/offer was made) be  $k$ , and the next spread at time  $t'$  (when the next bid/offer will be made) be  $k'$ . From Equation 6.10, it follows that  $k' = [1 - (t'/\tau)^\lambda]k_0$  and  $k_0 = \frac{k}{1 - (t/\tau)^\lambda}$ . With other market factors unchanged, an agent's next spread is:

$$k' = \frac{1 - (\frac{t'}{\tau})^\lambda}{1 - (\frac{t}{\tau})^\lambda} k \quad (6.11)$$

Thus, the concession factor *trading time and strategy* is formed by considering the changes of the spread current negotiation time  $t$  and the next negotiation round  $t'$  as follows:

$$T(t, t', \tau, \lambda) = \frac{1 - (\frac{t'}{\tau})^\lambda}{1 - (\frac{t}{\tau})^\lambda} \quad (6.12)$$

### 6.2.5 Eagerness

The concession factor *eagerness* considers an agent's desire to complete a negotiation and to make concessions during a negotiation. Let  $\varepsilon$  ( $0 \leq \varepsilon \leq 1$ ) represent the



percentage of convergence of the spread  $k$ , then the spread  $k'$  in the next negotiation round is given by  $k' = (1 - \varepsilon) \times k$ .  $\varepsilon$  corresponds to an agent's desire to make concession to narrow the differences between itself and others in each negotiation iteration, independent of the current trading time, number of competitors, and number of trading partners. The greater the value of  $\varepsilon$ , the more desire by an agent to make concession. In MDAs,  $\varepsilon$  is supplied by the user and is assumed to be a constant. The concession factor *eagerness* is represented as follows:

$$E(\varepsilon) = 1 - \varepsilon \quad (6.13)$$

### 6.2.6 Limitations of MDAs

In the above, we recapped the basics of MDAs. Now we disclose its limitations that may impact the negotiation outcomes. Even though the MDAs model has shown good performance [Sim04, Sim02, SW01], there still exist some limitations which may restrict its application in the real world. In fact, the current MDAs model cannot handle the situation where the negotiation environment becomes open and dynamic, and the outside options become uncertain. The main reason is that the current MDAs model does not employ any mechanism to handle possible changes on the negotiation environment. Therefore, when potential outside options become available in the future, agents cannot make reasonable responses to these changes, and cannot update their negotiation strategies according to these changes. For example, the concession factor *trading opportunity* is assessed by the total number of partners and spreads between an agent's offer and its partners' offers (see Equation (6.8)). However, it does not involve the forecast that partners may enter or leave the negotiation dynamically. Therefore, if the negotiation is processed with uncertain outside options, using these strategies agents cannot make effective decisions to change partners. Also, the concession factor *trading competition* cannot handle the situation where the number of partners and competitors are changed in the future. Thus, if the negotiation environment is changed, Equation (6.9) cannot represent the probability that an agent is being considered as the most preferred partner by all of its partners correctly anymore. Furthermore, for the concession factors *trading time and strategy* and *eagerness*, it will be more efficient for an agent to change its negotiation strategy and eagerness dynamically rather than keep these factors as constants when potential outside options are available. Therefore, in order to

remove the limitations mentioned above, an extended MDAs model is proposed in this chapter. Ways of modifying all concession factors are introduced in detail in the following section.

## 6.3 MDAs with Uncertain and Dynamic Outside Options

In this section, an extended MDAs model is introduced. The major approaches to modifying the concession factors *trading opportunity* (see Subsection 6.3.1) and *trading competition* (see Subsection 6.3.2) are: 1) to handle possible changes (i.e. uncertainties when negotiators will enter into or leave off the negotiation) on the negotiation environment; 2) to generate the corresponding reactions for each possible change; and 3) to make the final decision by combining all reactions based on their individual probabilities. The concession factors *trading time and strategy* (See subsection 6.3.3) and *eagerness* (See subsection 6.3.4) are modified based on the consideration that an agent may change its negotiation strategy and eagerness in order to reach an agreement.

### 6.3.1 Trading Opportunity

This subsection details how to modify the concession factor *trading opportunity* in an open and dynamic negotiation environment by considering the three cases: 1) the negotiating partners are allowed to enter negotiation only; 2) the negotiating partners are allowed to leave negotiations only; and 3) the negotiating partners are allowed to enter into and leave off negotiations at will.

#### Partners Enter into Negotiation Only

- **Only one partner enters into the negotiation:**

When only one partner enters the negotiation in the next round of negotiation, according to Equation (6.5) the aggregated conflict probability is:

$$P_c^1 = \prod_{i=1}^n p_i \times p_{n+1} \quad (6.14)$$

Since  $p_i$  ( $i \in [1, n]$ ) is already known, then the key point is how to obtain the conflict probability  $p_{n+1}$  for the new incoming partner. Because  $p_{n+1}$  is unknown until the next negotiation round, so we can determine an approximate value to replace  $p_{n+1}$  based on the situation of the current negotiation round. Let  $p_{n+1}^c$  be the most approximate value of  $p_{n+1}$  in all  $p_i$ , then any  $p_i$  has the same possibility ( $\frac{1}{n}$ ) to be  $p_{n+1}^c$ . Thus the mathematical expectation of  $p_{n+1}^c$  is  $\sum_{i=1}^n p_i/n$ . Because  $p_{n+1}^c$  is the approximation of  $p_{n+1}$ , then Equation (6.14) can be rewritten as:

$$P_c^1 = \prod_{i=1}^n p_i \times \frac{\sum_{i=1}^n p_i}{n} \quad (6.15)$$

Therefore, according to Equation (6.6), the extended *trading opportunity*, in the case of only one partner entering into the negotiation, is:

$$O(n, \omega_i, v) = \frac{1}{p'} \left( 1 - \prod_{i=1}^n p_i \times \frac{\sum_{i=1}^n p_i}{n} \right) \quad (6.16)$$

- **Only  $s$  partners enter into the negotiation:**

Similar to Equation (6.14), when exactly  $s$  partners enter the negotiation in the next round, under the independent assumption the aggregated conflict probability is:

$$P_c^s = \prod_{i=1}^n p_i \times p_{n+1} \times \dots \times p_{n+s} \quad (6.17)$$

The  $p_i$  ( $i \in [1, n]$ ) is known and each new incoming partner's ( $s_{n+k}, k \in [1, s]$ ) conflict probability  $p_{n+k}$  can be approximated by  $\sum_{i=1}^{n+k-1} p_i/(n+k-1)$  (similarly to  $p_{n+1}^c$ ). Thus Equation (6.17) can be expanded as:

$$P_c^s = \prod_{i=1}^n p_i \times \prod_{k=1}^s p_{n+k} = \prod_{i=1}^n p_i \times \prod_{k=1}^s \frac{\sum_{i=1}^{n+k-1} p_i}{n+k-1} \quad (6.18)$$

Therefore, *trading opportunity* can be rewritten when exactly  $s$  partners enter the negotiation, as follows:

$$O(n, \omega_i, v) = \frac{1}{p'} \left( 1 - \prod_{i=1}^n p_i \times \prod_{k=1}^s \frac{\sum_{i=1}^{n+k-1} p_i}{n+k-1} \right) \quad (6.19)$$

It can be seen that when  $k = 1$ , Equation (6.19) will be exactly the same as Equation (6.16).

- **At most  $m$  partners enter into the negotiation:**

When there are at most  $m$  partners, (the actual number of new incoming partners could be in  $[0, m]$ ) enter into the negotiation in the next round, if the probability of each partner entering the negotiation is  $p_{in}$ , then the extended concession factor *trading opportunity* is:

$$O(n, \omega_i, v)_{in} = \frac{1}{p'} \sum_{i=0}^m [C_m^i(p_{in})^i (1 - p_{in})^{m-i} \times (1 - \prod_{j=1}^n p_j \times \prod_{k=1}^i \frac{\sum_{j=1}^{n+i-1} p_j}{n+i-1})] \quad (6.20)$$

where  $C_m^i(p_{in})^i (1 - p_{in})$  is the probability that exactly  $i$  partners enter into the negotiation in the next round. Thus, Equation (6.20) includes all possible cases when at most  $m$  partners are allowed to enter the negotiation in the next round freely.

### Partners Leave off Negotiation Only

- **Only one partner leaves off the negotiation:**

When only one partner, say partner  $j$  leaves the negotiation in the next round, according to Equation (6.5) the aggregated conflict probability is  $\prod_{i=1, i \neq j}^n p_i$ . Because any one of the existing partners has the same probability ( $1/n$ ) to leave off the negotiation, then the aggregated conflict probability is:

$$p_c^1 = \sum_{i=1}^n \frac{\prod_{j=1, i \neq j}^n p_j}{n} \quad (6.21)$$

Therefore, according to Equation (6.6), the extended *trading opportunity*, in the case of only one partner leaving off the negotiation, is:

$$O(n, \omega_i, v) = \frac{1}{p'} \left( 1 - \sum_{i=1}^n \frac{\prod_{j=1, i \neq j}^n p_j}{n} \right) \quad (6.22)$$

- **Only  $s$  partners leave off the negotiation:**

When there are exactly  $s$  ( $0 \leq s \leq n$ ) partners leaving off the negotiation in the next round, let  $\mathbf{p}$  be the set of all existing partners in the current round,  $\varphi_s$  be the set of partners leaving, and  $\bar{\varphi}_s$  be the set of partners that stay in the next round ( $\varphi_s \cup \bar{\varphi}_s = \mathbf{p}$  and  $\varphi_s \cap \bar{\varphi}_s = \emptyset$ ). According to Equation (6.5), the aggregated conflict probability, when exactly  $s$  ( $\varphi_s$ ) leave off the negotiation, is  $\prod_{i \in \bar{\varphi}_s} p_i$ . Thus the extended *trading opportunity*, by considering exactly  $s$  partners leaving off the negotiation, is:

$$O(n, \omega_i, v) = \frac{1}{p'} \left( 1 - \sum_{i=1}^{C_n^s} \frac{\prod_{j \in \bar{\varphi}_s^i} p_j}{C_n^s} \right) \quad (6.23)$$

where  $C_n^s$  is the number of possible combinations from the set  $\mathbf{p}$  with  $n$  elements. It can be seen that when  $s = 1$ , Equation (6.23) will be exactly the same as Equation (6.22).

- **At most  $m$  partners leave off the negotiation:**

When at most  $m$  ( $0 \leq m \leq n$ ) partners leave off the negotiation in the next round (the actual number of partners leaving could be between 0 and  $n$ ), if the probability of each partner leaving the negotiation is  $p_{out}$ , then the concession factor *trading opportunity* is:

$$O(n, \omega_i, v)_{out} = \frac{1}{p'} \sum_{i=0}^m [C_m^i (p_{out})^i (1 - p_{out})^{m-i} \times (1 - \sum_{j=1}^{C_m^i} \frac{\prod_{k \in \bar{\varphi}_i^j} p_k}{C_m^i})] \quad (6.24)$$

where  $C_m^i (p_{out})^i (1 - p_{out})^{m-i}$  is the probability that exactly  $i$  partners leave the negotiation in the next round. Therefore, Equation (6.24) includes all possible situations when at most  $m$  partners leave off the negotiation.

### Partners Enter into and Leave off Negotiation Freely

When there are at most  $m$  partners entering into the negotiation and/or leaving off the negotiation as they wish, the extended *trading opportunity*, by considering all situations mentioned above (i.e. Equations (6.20) and (6.24)) is:

$$O(m, \omega_i, v)_{all} = O(n, \omega_i, v)_{in} \times w_{in} + O(n, \omega_i, v)_{out} \times w_{out} \quad (6.25)$$

where  $w_{in} \in [0, 1]$ ,  $w_{out} \in [0, 1]$ , and  $w_{in} + w_{out} = 1$ , represent the significance of each individual situation. Usually, both of them are simply assigned as 0.5 to indicate that the same attention is paid to both incoming and outgoing changes.

### 6.3.2 Trading Competition

In this subsection, we extend the concession factor of *trading competition* by following a similar method to extending *trading opportunity*. There are three cases that need to be considered, namely: (1) only competitors change; (2) only partners change; and (3) both competitors and partners change.

#### Only Competitors Change

In the first instance, we will consider the situation where the number of competitors changes during the negotiation only.

- **At most  $q$  competitors enter into the negotiation:**

When at most  $q$  competitors enter the negotiation, the probability that the agent is considered as the most preferred trader by at least one of their partners (see Subsection 6.2.3) is:

$$C_{cin}(m, n) = \sum_{i=0}^q [C_q^i(p_{in})^i (1 - p_{in})^{q-i} \times (1 - (\frac{m+i-1}{m+i})^n)] \quad (6.26)$$

where  $1 - (\frac{m+i-1}{m+i})^n$  is the *trading competition* factor when exactly  $i$  ( $i \in [0, q]$ ) competitors enter the negotiation.

- **At most  $p$  competitors leave off the negotiation:**

When there are at most  $p$  competitors leaving the negotiation, then the probability that the agent is considered as the most preferred trader by at least one partner is:

$$C_{cout}(m, n) = \sum_{i=0}^p [C_p^i(p_{out})^i (1 - p_{out})^{p-i} \times (1 - (\frac{m-i-1}{m-i})^n)] \quad (6.27)$$

where  $1 - (\frac{m-i-1}{m-i})^n$  is the *trading competition* factor when exactly  $i$  ( $i \in [1, p]$ ) competitors leave off the negotiation.

- **Competitors enter into and leave off the negotiation freely:**

Based on the considerations about the two situations mentioned above (see Equations (6.26) and (6.27)), when competitors are allowed to enter into and leave off the negotiation freely, the *trading competition* is represented as:

$$C_c(m, n) = C_{cin}(m, n)w_{in} + C_{cout}(m, n)w_{out} \quad (6.28)$$

where  $w_{in}$  and  $w_{out}$  are weights. The default values are 0.5 for equal weighting.

### Only Partners Change

In the second stage, we keep the number of competitors unchanged, but take into account the situation where the number of partners change.

- **At most  $w$  partners enter into the negotiation:**

When there are at most  $w$  partners entering the negotiation, then the probability that the agent is considered as the most preferred partner by at least one partner is:

$$C_{pin}(m, n) = \sum_{i=0}^w [C_w^i(p_{in})^i (1 - p_{in})^{w-i} \times (1 - (\frac{m-1}{m})^{n+i})] \quad (6.29)$$

where  $1 - (\frac{m-1}{m})^{n+i}$  is the *trading competition* factor when exactly  $i$  partners enter the negotiation.

- **At most  $v$  partners leave off the negotiation:**

When there are at most  $v$  partners leaving off the negotiation, the concession factor *trading competition* is:

$$C_{pout}(m, n) = \sum_{i=0}^v [C_v^i(p_{out})^i (1 - p_{out})^{v-i} \times (1 - (\frac{m-1}{m})^{n-i})] \quad (6.30)$$

where  $1 - (\frac{m-1}{m})^{n-i}$  is the *trading competition* factor when exactly  $i$  partners leave off the negotiation.

- **Partners enter into and leave off the negotiation freely:**

Based on the two considerations mentioned above (see Equations (6.29) and (6.30)), by considering the change of partners only, the concession factor *trading competitor* is:

$$C_p(m, n) = C_{pin}(m, n)w_{in} + C_{pout}(m, n)w_{out} \quad (6.31)$$

where  $w_{in}$  and  $w_{out}$  are weights. The default values are 0.5 for equal weighting.

### Both Competitors and Partners Change

In the last stage, we combine all situations and allow both competitors and partners to change freely. Then the probability that the agent is considered as the most preferred trader by at least one of their partners is:

$$C(m, n) = C_c(m, n)w_c + C_p(m, n)w_p \quad (6.32)$$

where  $C_c(m, n)$  is defined by Equation (6.28),  $C_p(m, n)$  is defined by Equation (6.31), and  $w_c$  and  $w_p$  are the weights on each term.

### 6.3.3 Trading Time and Strategy

In this subsection, the concession factor *trading time and strategy* is extended by considering changes of the parameter  $\lambda$ . According to the explanation of  $\lambda$  (see Equation (6.10)), the bigger the value of  $\lambda$ , the smaller the concession agents will give in the early negotiation round, and the larger the concession agents will give in the later negotiation round, and vice versa. Furthermore, if the value of concession factors *trading opportunity* and *trading competition* changes, the amount of concession should also be changed. Therefore, the parameter  $\lambda$  should be determined by both *trading opportunity* and *trading competition*. Accordingly, the extended *trading time and strategy* is:

$$T(t, t', \tau, \lambda_t) = \frac{1 - (\frac{t'}{\tau})^{\lambda_{t'}}}{1 - (\frac{t}{\tau})^{\lambda_t}} \quad (6.33)$$

where  $\lambda_t$  is calculated by:

$$\lambda_t = \lambda_0 \times O_t(n, \omega_i, v) \times C_t(m, n) \quad (6.34)$$



where the  $\lambda_0$  is the initial value of the concession, and is assigned by the user.  $O_t(n, \omega_i, v)$  is the factor *trading competition* at negotiation round  $t$  (see Equation (6.32)), and  $C_t(m, n)$  is the factor *trading opportunity* at negotiation round  $t$  (see Equation (6.25)). Equation (6.34) indicates that when the number of partners is greater than the number of competitors during a negotiation (positive to the agent), in order to maximize its profit, the agent should decrease its concession. However when the number of partners is less than the number of competitors, the agent should give more concession in order to keep its partners.

### 6.3.4 Eagerness

In this subsection, the concession factor of *eagerness* is extended by considering changes in the negotiation environment. The general idea of the extension is that: according to economists, people's eagerness to complete a trade should be directly related to their benefits. So it is proposed to extend *eagerness* by considering agents' benefits. In each negotiation round, when an agent's benefits are changed by partners' offers, the agent's eagerness to reach an agreement should also be changed. Let  $br_t$  ( $br_t > 0$ ) denote the ratio between an agent's maximal benefits in two conjoint negotiation rounds;  $br_t$  can be calculated as:

$$br_t = \frac{mb_t}{mb_{t*}} \quad (6.35)$$

where  $mb_t$  is the agent's maximal benefit in the current round, and  $mb_{t*}$  is the maximal benefit in the last round. Both  $mb_t$  and  $mb_{t*}$  can be easily gained from the negotiation records. Then the factor of *trading eagerness* is extended as:

$$E(\varepsilon_t) = 1 - \varepsilon_t \quad (6.36)$$

where

$$\varepsilon_t = \begin{cases} \varepsilon_0 & t = 0 \\ \varepsilon_{t-1} \times br_t & t > 0 \end{cases} \quad (6.37)$$

where  $\varepsilon_0$  is the initial value of *eagerness* and is assigned by the user. From Equations (6.37) and (6.35), it can be seen that the more benefits the agent gains than the last negotiation round, the more eagerness that the agent wants to reach an agreement for the negotiation. For example, when  $br_t > 1$ , this indicates that the agent's benefit

is increased in the current round, so the agent will be more eager to complete the trading; when  $0 < br_t < 1$ , this indicates that the agent's benefit is decreased in the current round, so the agent will be less eagerness to complete the trading; and when  $br_t = 1$ , this indicates that the agent's benefit does not change in the current round, so the agent will not change its eagerness. The purpose of this updating strategy on  $\varepsilon_t$  is to help agents modify their eagerness as the negotiation environment changes.

### 6.3.5 Discussion

In this section, we introduced the extended MDAs model by considering dynamic changes in the negotiation environment. By comparison with the original MDAs model, each concession factor has been extended as follows:

- **Trading opportunity**  
By employing the extended MDAs model, an agent can calculate the trading opportunity in the current negotiation round, and can also handle changes of trading opportunity. The agent can handle the opportunity of completing the negotiation in future rounds. Then the agent can modify its negotiation strategy in order to maximize self profits and ensure an agreement can be achieved successfully as well.
- **Trading competition**  
The agent can handle future situations of competition in the dynamic negotiation environment. In multi-lateral negotiation, competition is a very significant issue, and impacts on both the negotiation strategy and the result. By employing the extended MDAs model, an agent can gain more advantages during competitions.
- **Trading time and strategy**  
In the original MDAs model, the agent's negotiation strategy is predefined by the client and will not be changed throughout the negotiation. However, in an open and dynamic negotiation environment, a constant negotiation strategy cannot respond to changes in the environment, so the agent may face loss of profits or negotiation partners. In the extended MDAs model, we improve this factor and agents are allowed to modify their negotiation strategies according to a changing environment. Therefore, the agent can get more advantages in

open and dynamic negotiation by employing the extended MDAs model rather than the original MDAs model;

- **Eagerness**

In the original MDAs model, the eagerness of an agent to complete a negotiation is also predefined by the client. However, in reality, an agent's eagerness to complete the negotiation should be impacted by the negotiation environment and the benefits the agent can gain. Usually, agents prefer higher benefits. In the extended MDAs model, we take account of this situation and allow an agent to modify its *eagerness* when a negotiation environment changes.

## 6.4 Experiments

In this section, we illustrate our experimental results based on each of the four concession factors. These are *trading opportunity* (see Subsection 6.4.2), *trading competition* (see Subsection 6.4.3), *trading time and strategy* (see Subsection 6.4.4) and *eagerness* (see Subsection 6.4.5). In Subsection 6.4.6, experimental results by combining all concession factors are illustrated.

### 6.4.1 Setup of Experiments

Firstly, we briefly introduce the setup of our experiments:

1. Negotiation participators are divided into two types, namely “partners” and “competitors”; the initial numbers for both are 5.
2. The maximum number of agents that can enter or leave the negotiation is between 0 and 5, which is from 0% to 100% of the initial number.
3. The probability that an agent will enter into or leave off the negotiation is assigned to 0.5.
4. The maximum negotiation round is assigned to 10.
5. It is only assumed that both the number of partners and number of competitors are always greater than 0; there is no assumption about agents' negotiation strategies and protocols.

### 6.4.2 Experiment 1: Trading Opportunity

According to Subsection 6.3.1, the concession factor *trading opportunity* only considers changes of partners. In this subsection, experiments are illustrated to test the performance of the proposed extension approach on *trading opportunity*.

- **Partners can only enter into the negotiation:**

In this experiment, partners are only allowed to enter the negotiation. The experimental results are displayed in Figure 6.3. The x-axis indicates the negotiation round, while the y-axis is the value of *trading opportunity*. The higher the value of *trading opportunity*, the more possibility that agents can finish the negotiation. When only one partner (10% of initial partners) enters the negotiation, the negotiation success rate increases significantly. As the number of entering partners increases, the success rate also increases. However, the increment becomes slow. The reason is that no matter how many prospective partners exist, only one agreement can be reached with one partner. Therefore, it is noticed that there is a bottleneck between the number of prospective partners and the negotiation success rate. When the number of prospective partners is higher than a threshold (60% of initial partners), its effect will not be so significant as it used to be. In this case, agents have to seek another approach to increase their negotiation success rate. Furthermore the experimental result indicates that in a negotiation, especially in an open and dynamic environment, agents do not need to undertake a comprehensive investigation of all prospective partners. A reasonable search for prospective partners within the local society is adequate to keep the negotiation success rate at a desirable level.

- **Partners can only leave off the negotiation:**

In this experiment, partners are only allowed to leave off the negotiation. The experimental results are displayed in Figure 6.4. It can be seen that as the number of leaving partners increases, the negotiation success rate keeps decreasing. When only one partner (10% of initial partners) leaves the negotiation, the negotiation success rate decreases by more than one third. As the number of leaving prospective partners increases, the negotiation success rate drops quickly. When the number of leaving partners is larger than three (60% of initial partners), the success rate decreases very little compared to the

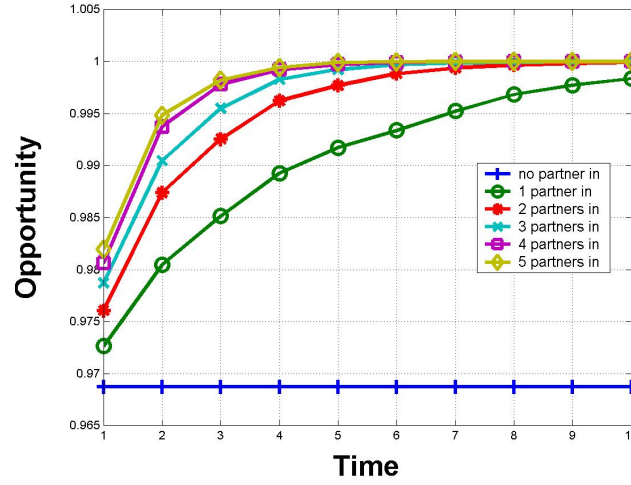


Figure 6.3: Trading opportunity when partners enter freely.

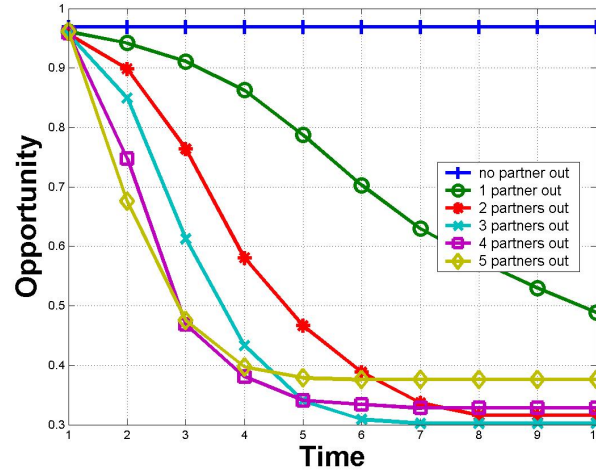


Figure 6.4: Trading opportunity when partners leave freely.

original one. Therefore, the experimental result indicates that in order to ensure success of the negotiation, agents should keep the number of prospective partners to a reasonable level.

- **Partners can enter into and leave off the negotiation:**

In this experiment, partners can enter into and leave off the negotiation freely. In Figure 6.5, it can be seen that as the number of entering and leaving prospective partners increases, the negotiation success rate decreases. However, even for the most complex situation, at most five prospective agents (100% of initial partners) can enter and leave the negotiation freely, the decrease in negotiation

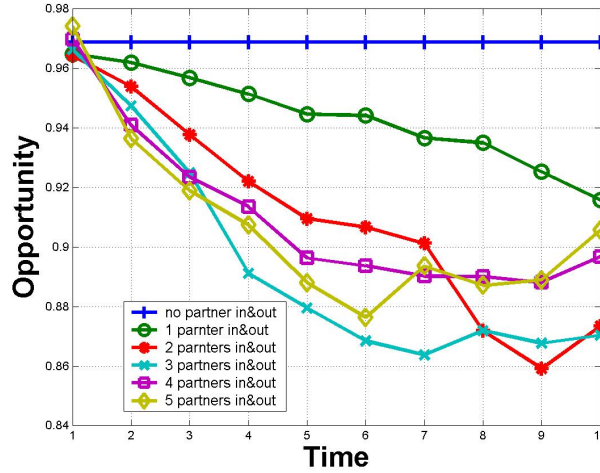


Figure 6.5: Trading opportunity when partners enter and leave freely.

success rate is only 10%. This experimental result indicates that in an open and dynamic environment, when the number of prospective partners fluctuates, negotiation success will be impacted only minimally. The reason could be that (1) when the new incoming partners replace existing ones, the uncertainty of the new incoming partner's bids will impact on the negotiation success rate; and (2) since competitors also exist during the negotiation, the new incoming partners may have more interest in other competitors. Therefore, fluctuation of the environment may have very little impact on the negotiation success rate. In order to maintain the success rate, agents should retain their prospective partners as much as they can.

According to the experimental results in this subsection, it can be seen that the proposed approach successfully handles uncertainties in the negotiation environment, and helps agents to update their negotiation strategies to increase the negotiation success rate.

### 6.4.3 Experiment 2: Trading Competition

According to Subsection 6.3.2, both partners and competitors can impact on the value of *trading competition*. Therefore, we test the extended approach on *trading competition* by considering changes on both partners and competitors.

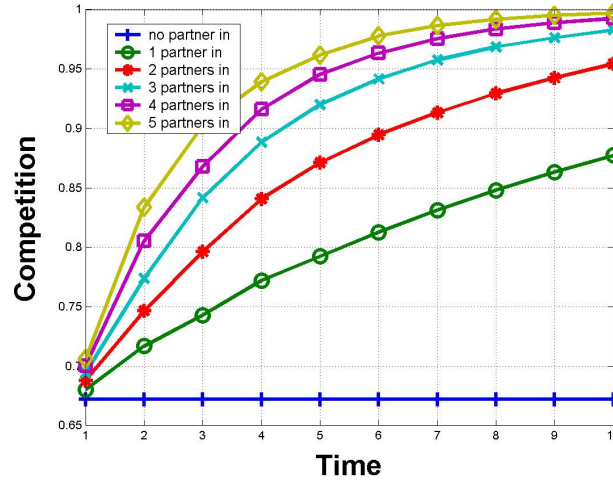


Figure 6.6: Trading competition when partners enter freely.

### Considering partners only

In this part, only changes of partners are considered, and the number of competitors is kept as a constant.

- **Partners can only enter into the negotiation**

In this experiment, partners are only allowed to enter the negotiation. The experimental results are displayed in Figure 6.6. The higher the value of *trading competition*, the less competition the agent will meet during negotiation. In Figure 6.6, it can be seen that as the number of prospective partners increases, the agent will face less competition during the negotiation. When two prospective partners (40% of initial partners) enter the negotiation, the value of *trading competition* is increased by more than 50%. However, when the number of incoming partners is bigger than three (60% of initial partners), the value of trading competition is not increased significantly. This experiment result is very similar to the experiment on *trading opportunity*. It indicates that when the number of prospective partners is bigger than a threshold, the increase in the number of partners will have little impact on agent competition. In this case, the method of eliminating existing competitors will have more effect on decreasing agents' competition in the negotiation.

- **Partners can only leave off the negotiation**

In this experiment, partners are only allowed to leave the negotiation. The

experimental results are displayed in Figure 6.7. It can be seen that as the number of prospective partners decreases, agents will face more competition during the negotiation. In general, each 20% loss of prospective partners will increase similar pressure on agent competition.

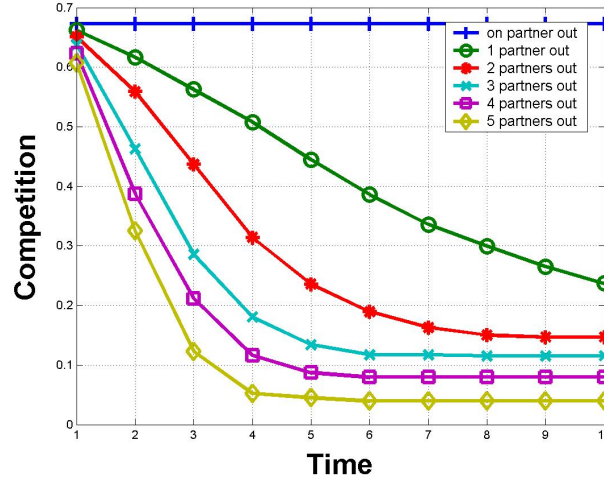


Figure 6.7: Trading competition when partners leave freely.

- **Partners enter into and leave off the negotiation**

In this experiment, partners can enter and leave the negotiation freely. In Figure 6.8, it can be seen that as the number of prospective partners fluctuates, the agent's competition will increase slightly on average, but will also fluctuate. The more changes in the negotiation environment, the more fluctuation will occur. Also this experiment obtains a similar result as the experiment on *trading opportunity*, which is that fluctuation of perspective partners in the negotiation environment has very little impact on agent competition during negotiation.

### Considering competitors only

In this part, only changes of competitors are considered; the number of partners remains constant.

- **Competitors can only enter into the negotiation**

In this experiment, competitors are only allowed to enter the negotiation. The experimental results are displayed in Figure 6.9, which indicates that the more



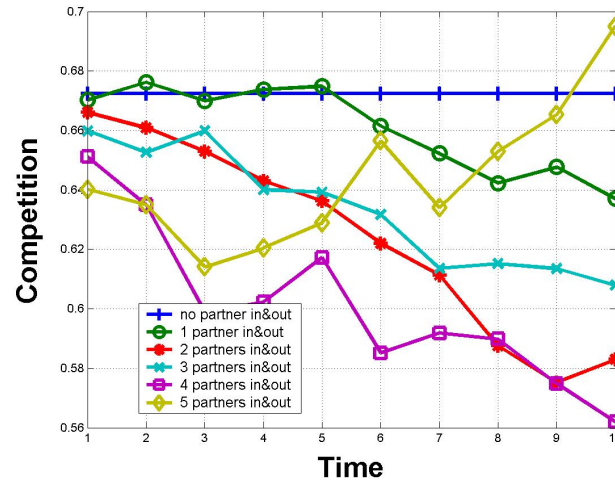


Figure 6.8: Trading competition when partners enter and leave freely.

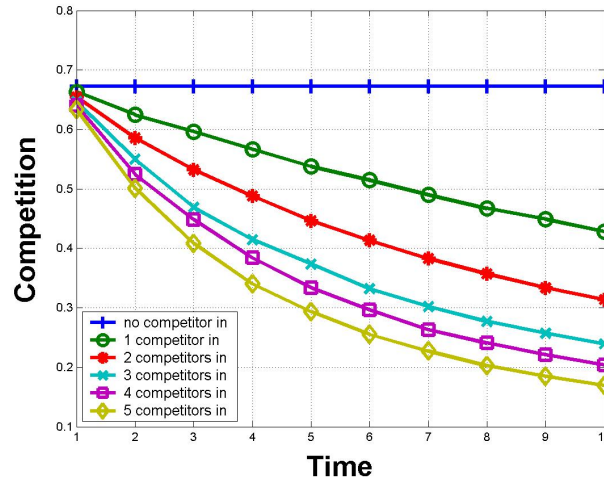


Figure 6.9: Trading competition when competitors enter freely.

competitors entering the negotiation, the more competition agents will face. A 40% increase in the number of competitors can increase competition by more than 50% during negotiation.

- **Competitors can only leave off the negotiation**

In this experiment, competitors are only allowed to leave the negotiation. The experimental results displayed in Figure 6.10 indicate that as the number of competitors decreases, the competition between agents also decreases. Each 20% loss of the number of competitors will release agents' pressure to a similar level.

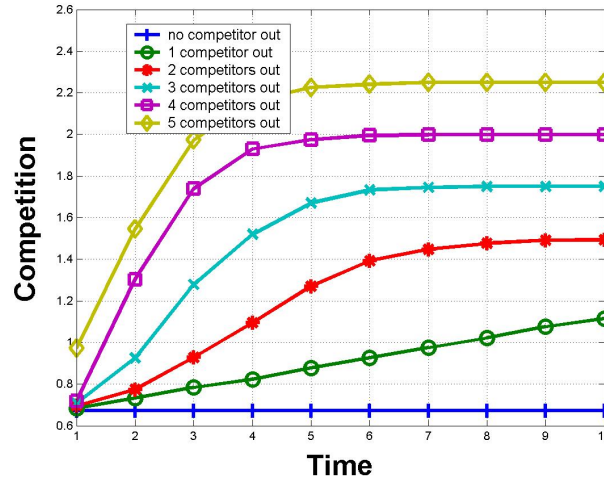


Figure 6.10: Trading competition when competitors leave freely.

- **Competitors enter into and leave off the negotiation**

In this experiment, competitors can enter and leave the negotiation freely. The experimental results are displayed in Figure 6.11. In contrast to the experimental results on partners, the fluctuation on the number of competitors has considerable impact on agent competition. The more competitors that are allowed to enter and leave the negotiation freely, the less competition agents will meet during the negotiation. The leaving competitors can release pressure immediately, but the incoming competitors cannot exert more pressure to the existing agents in a short time. Therefore, changes in the number of competitors can take benefits to both the negotiation participators and the whole market.

### Considering both partner and competitor

In this part, both changes of partners and competitors are considered. As shown in Figure 6.12, when both partners and competitors can enter and leave during the negotiation freely, the values of *trading competition* fluctuate relative to the original value. The more changes of negotiation participators, the more complex the situation will be and the bigger the fluctuation. It can be seen that our experimental results, which indicate the relationship between negotiation environment and agent pressure, are reasonable. This relationship can be employed by agents to modify their negotiation strategies when the negotiation environment changes.

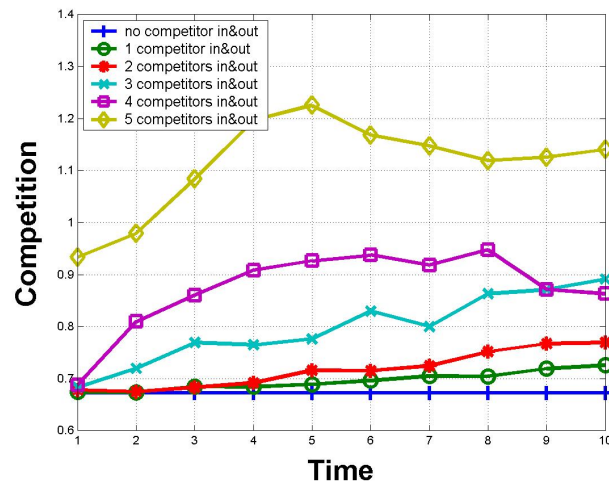


Figure 6.11: Trading competition when competitors enter and leave freely.

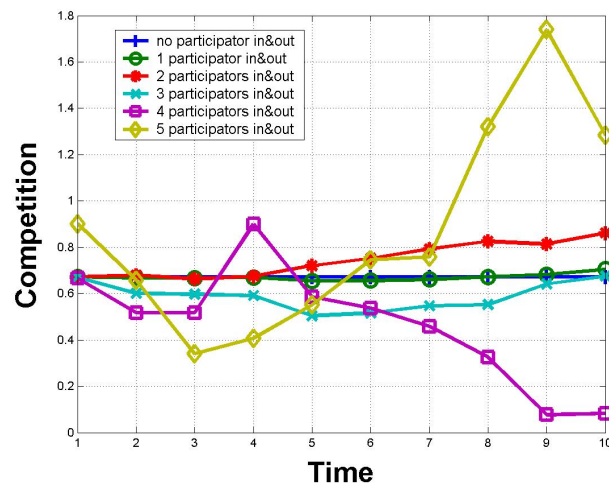


Figure 6.12: Trading competition when both partners and competitors enter and leave freely.

### 6.4.4 Experiment 3: Trading Time and Strategies

According to Subsection 6.3.3, both the number of partners and competitors can impact on the value of *trading time and strategy*. What is more, the values of *trading time and strategy* are also dependent on the parameter  $\lambda$  and the remaining time. Therefore, we test the proposed approach in terms of changes of partners and competitors, respectively.

#### Considering partners only

In this part, only the changing of partners is considered, and not the changing of competitors.

- **Partners can only enter into the negotiation**

In this experiment, partners are only allowed to enter the negotiation. The experimental results are displayed in Figure 6.13. The x-axis indicates the negotiation time, while the y-axis is the value of  $\lambda$  (see Subsection 6.2.4). The higher the value of  $\lambda$ , the less concession the agent will make in the early round, and conversely. As shown in Figure 6.13, when the number of prospective partners increases, much less concession will be made in the early rounds. That is because the agents' *trading opportunity* is increased and *trading competition* is decreased. Therefore agents make a decision to decrease their concession in order to enlarge their benefits. The more prospective partners that enter the negotiation, the less concession the agent concedes.

- **Partners can only leave off the negotiation**

By contrast, while partners are only allowed to leave the negotiation, agents should enlarge their concession in order to increase the negotiation success rate. The experimental results are displayed in Figure 6.14. It can be seen that as the number of prospective partners decreases, much larger concession is made during the early rounds.

- **Partners can enter into and leave off negotiation**

In this experiment, partners can enter into and leave off the negotiation freely. The experimental results are displayed in Figure 6.15. It can be seen that as the number of prospective partners fluctuates, the value of  $\lambda$  is slightly decreased. The reason for this is that when the number of prospective partners

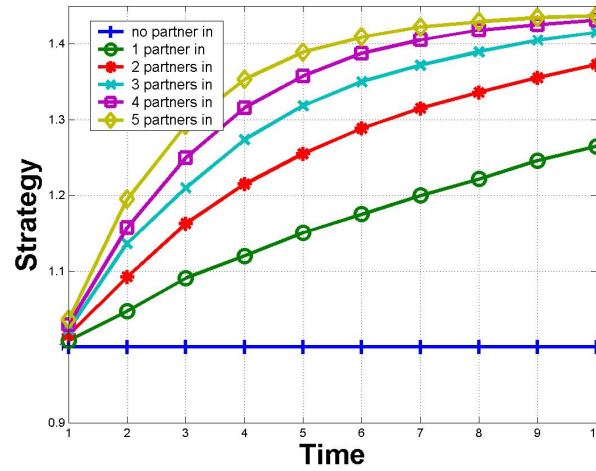


Figure 6.13: Trading strategy when partners enter freely.

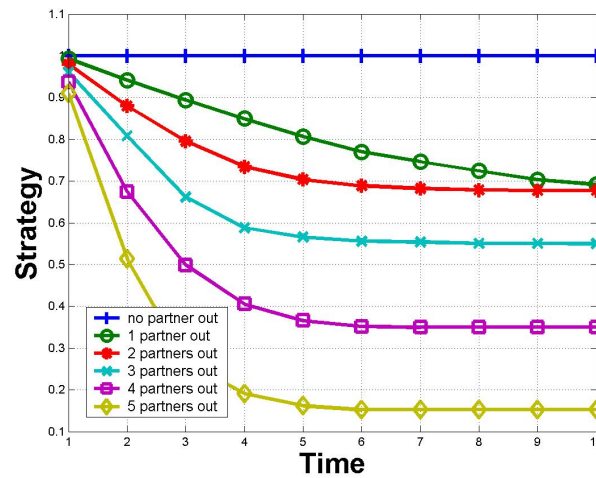


Figure 6.14: Trading strategy when partners leave freely.

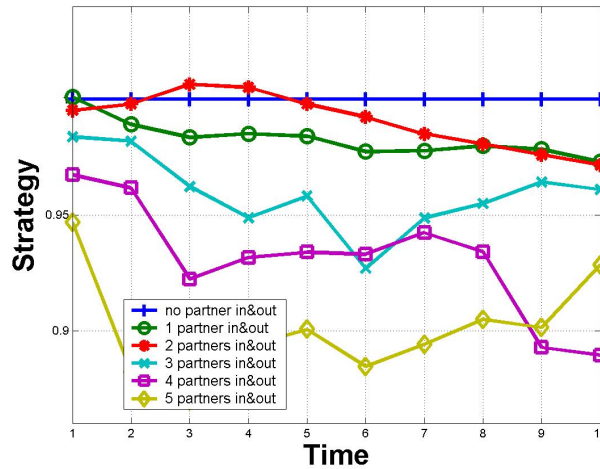


Figure 6.15: Trading strategy when partners enter and leave freely.

is changed, the agent's *trading opportunity* is decreased (see experiments on *trading opportunity* Subsection 6.4.2) and its *trading competition* is increased (see experiments on *trading competition* Subsection 6.4.3). Therefore agents have to increase their concession to respond to such changes.

### Considering competitors only

In this part, only changes of competitors are considered, not changes of partners.

- **Competitors can only enter into the negotiation**

In this experiment, competitors are only allowed to enter the negotiation. In Figure 6.16, it can be seen that the results are very similar to the situation where partners are only allowed to leave the negotiation freely. When the total number of competitors increases, agents tend to increase their concession from the early negotiation rounds.

- **Competitors can only leave off the negotiation**

In this experiment, competitors are only allowed to leave the negotiation. In Figure 6.17, it can be seen that as the total number of competitors decreases, agents tend to give less concession during the early rounds of the negotiation. This is very similar to the situation where prospective partners are allowed to enter the negotiation freely.

- **Competitors enter into and leave off the negotiation**

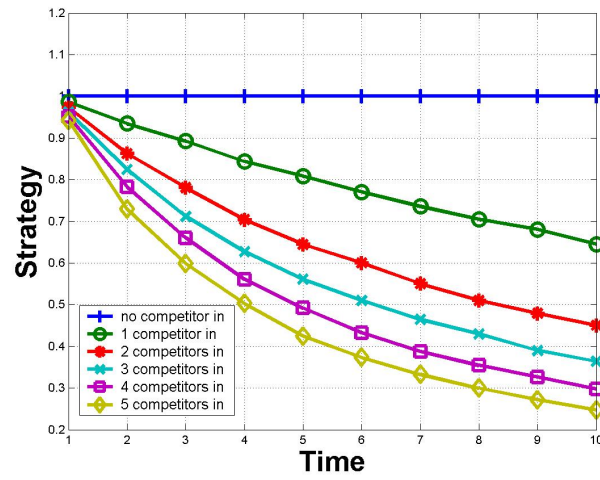


Figure 6.16: Trading strategy when competitors enter freely.

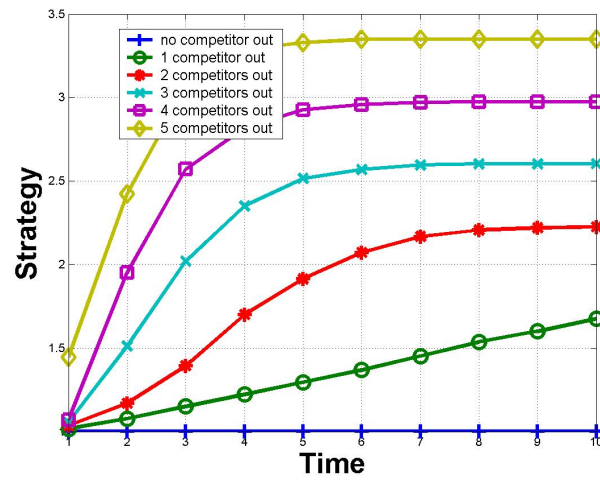


Figure 6.17: Trading strategy when competitors leave freely.

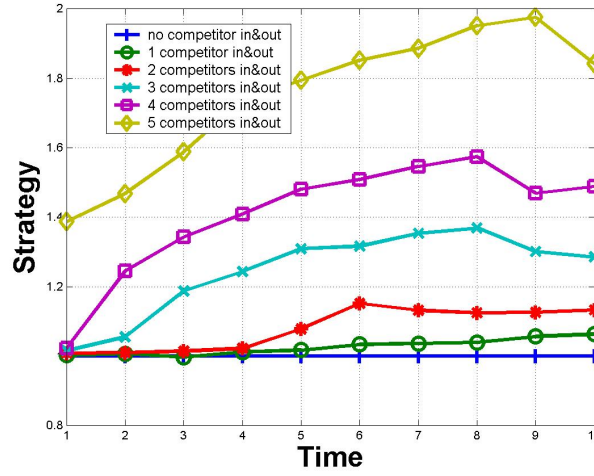


Figure 6.18: Trading strategy when competitors enter and leave freely.

When competitors can enter and leave the negotiation freely, the experimental results are displayed in Figure 6.18. It can be seen that as the total number of competitors fluctuates, agents increase the value of  $\lambda$  and decrease their concession from the early rounds. Similar to the experiments on *trading competition* (see Subsection 6.4.3), the explanation of these results is that the leaving competitors can release the pressure from agents immediately, but incoming competitors cannot place more pressure on agents in the short term. Therefore, agents tend to decrease their concession level.

### Considering both partner and competitor

In this part, changes of both partners and competitors are considered. As shown in Figure 6.19, when both partners and competitors can enter and leave the negotiation freely, agents' strategies on the amount of concession also fluctuate relative to their initial values. The more changes in the number of participators, the bigger the fluctuation will be. Therefore, in an open and dynamic environment, agents need a proper approach to estimate the potential changes of the negotiation environment and to make reasonable responses.

#### 6.4.5 Experiment 4: Eagerness

In this subsection, we perform experiments to test the proposed approach on *eagerness*. According to Subsection 6.3.4, the value of *eagerness* will be impacted by



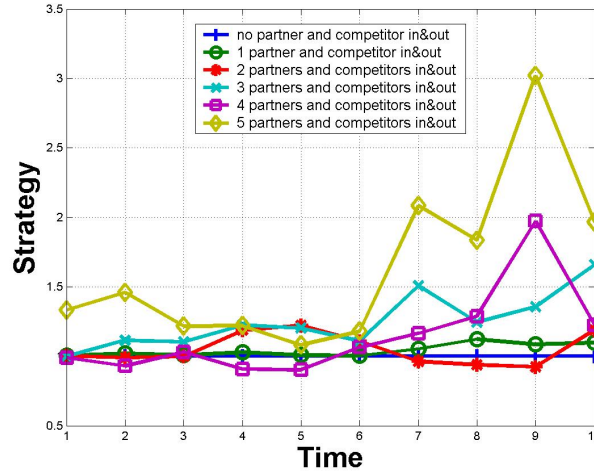


Figure 6.19: Trading strategy when both partners and competitors enter and leave freely.

benefit ratio  $br_t$ . In order to simplify the experiment, we set  $br_t$  to 0.5, 1 and 2 respectively, and compare them. In fact, the value of  $br_t$  is changed dynamically in each negotiation round.

In Figure 6.20, it can be seen that as the value of benefit ratio increases, the value of *eagerness* also increases and the agents are more eager to finish the negotiation. Therefore, it can be seen that the proposed approach successfully adjusts the value of *eagerness* according to the agents' negotiation environment.

#### 6.4.6 Experiment 5: Combining all factors

In this subsection, we illustrate the experimental results by combining all concession factors in Figure 6.21. It can be seen that when only 1 (i.e., 20%) or 2 (i.e., 40%) negotiation participator/s enters/enter into or leaves/leave off the negotiation freely, the agent can decrease its concession by comparison with the original MDAs model. The reason behind this result is that when few negotiation participators can enter into or leave off the negotiation freely, the agent will get more chances to find a 'better' negotiation partner. Even though the existing negotiation partner may leave off the negotiation as well, the negotiation partners with higher opportunity may not leave off the negotiation, so the agent will not be impacted too much by existing partners' leaving. On the other hand, pressure from the negotiation competitors is not so heavy because as shown in Figure 6.8, when at most 1 (i.e., 20%) or 2 (i.e., 40%) competitor/s enters/enter into or leaves/leave off the negotiation freely, the

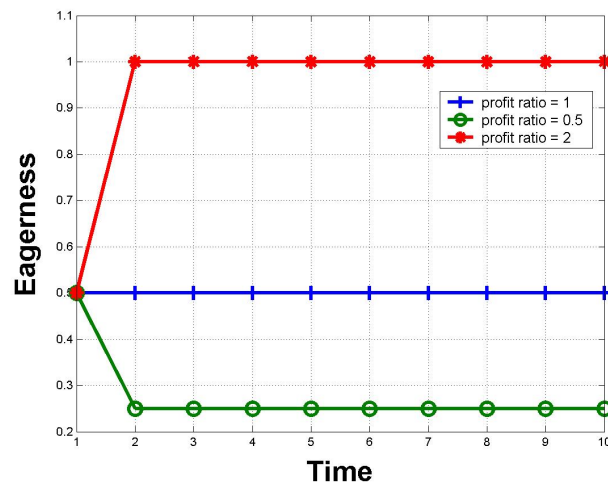


Figure 6.20: Eagerness.

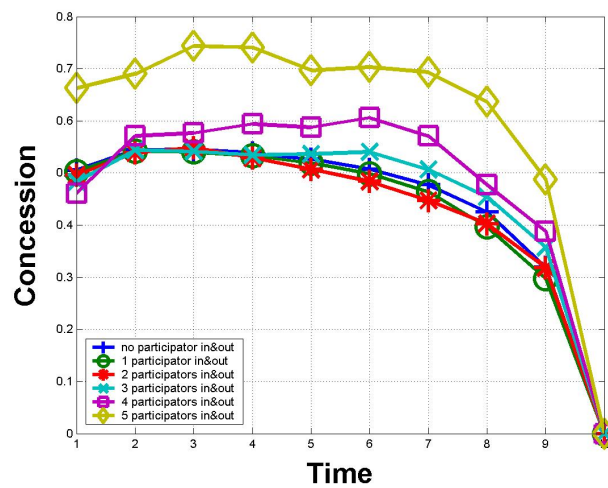


Figure 6.21: Combine all factors.

agent will not obtain too much competition in the environment. However, when there are more than 3 (i.e., 60%) negotiation participators who enter into or leave off the negotiation freely, the situation changes. The agent has to face more pressure from competitors, and existing partners with higher opportunity may also leave off the negotiation, so in order to ensure that the negotiation can reach an agreement, the agent has to increase its concession. It can be seen from the curve that for each increment (10% of all negotiation participators) on changing the number of negotiation participator, the agent has to increase its concession value by 10% of its maximum concession on average. In the extreme case, when at most 5 participators can enter into or leave off the negotiation, the agent has to make 20% more concession to its negotiation partners compared with the original MDAs model in order to ensure that negotiation agreement can be reached successfully.

In this section, we illustrate the experimental results on each individual concession factor, as well as the combined factors. In general, from the experimental results, it can be seen that when less than 40% of negotiation participators may enter into or leave off the negotiation, the agent's negotiation strategy does not necessarily need much updating. Furthermore, a little change of the negotiation environment may bring some advantages to most negotiation participators. However, when more than 40% of negotiation participators may enter into or leave off the negotiation, an agent has to modify its strategy in order to reach an agreement. Usually, a big change in the negotiation environment has a negative impact on most negotiation participators.

## 6.5 Summary

In this chapter, four concession factors in MDAs (namely *trading opportunity*, *trading competition*, *trading time and strategy* and *eagerness*) were modified by taking into account uncertain and dynamic outside options. In an open and dynamic negotiation environment, negotiators were allowed to enter and leave a negotiation freely. Through analyzing the uncertain negotiation environment, the proposed approach can generate reasonable decisions to update agents' strategies in a dynamic environment. The experimental results also illustrated both the efficiency and accuracy of the proposed approach.

## Market-Based Strategy for Multilateral Multiple Issue Negotiation

### 7.1 Introduction

Electronic commerce has changed traditional methods of business in recent years and has become a very important commercial phenomenon. Nowadays, many businesses operate in e-marketplaces and intelligent agents can help businesses to make e-trading more efficient. Due to different interests in trades, negotiation mechanisms are normally adopted by agents to communicate and compromise to reach mutually beneficial agreements when conflicts happen. In a dynamic electronic marketplace, people can easily access the e-market to publish information, to retrieve items of interest, to negotiate with opponents synchronously and to terminate any ongoing negotiation freely. In Chapter 6, a market-driven negotiation model was introduced to consider the uncertainty of a dynamic negotiation environment. However, the market-driven negotiation model proposed in Chapter 6 considered only negotiations with a single issue, but did not take multiple issues into account. The major differences between single issue negotiation and multi-issue negotiation is that: (1) multi-issue negotiation between intelligent agents can lead negotiators to ‘win-win’ negotiation outcomes, which can hardly be achieved by single issue negotiation [LSL07]; (2) multi-issue negotiation can process multiple issues synchronously. In an e-marketplace, multi-issue negotiation can definitely help agents to improve their negotiation outcomes as well as the negotiation efficiency. Therefore, this chapter tries to propose a model to solve a research issue in agent negotiation by considering both multiple issues and the uncertainty of negotiation.

Although researchers have successfully proposed many multi-issue negotiation models from different considerations, very few of them consider dynamic e-market

environments and multiple preferences. Fatima et al. [FWJ07] proposed a multi-issue negotiation model to achieve optimal negotiation outcomes for online negotiation. However, their model only worked in the situation of bilateral negotiation without consideration of dynamic changes of negotiation environments. Lai et al. [LSL07, LLS06] presented a model for multi-attribute negotiations between two negotiators. However, impacts on negotiators' strategies from outside options are still not taken into account. Hemaissia et al. [HSLM07] proposed a multilateral multi-issue negotiation protocol in a cooperative scenario by employing a mediator agent. However, when the number of negotiation participators fluctuates, the mediator can hardly make an unbiased and accurate response to all negotiators. Fatima et al. [FWJ02, FWJ04a] studied negotiation models in incomplete information settings in different negotiation scenarios and illustrated equilibrium solutions for different negotiation agendas and procedures. However, their work only presented multi-issue negotiation in static negotiation environments.

In this chapter, a market-based multiple-offer model for multi-issue negotiation in a complex environment was proposed to help negotiators to make wiser decisions during negotiations by considering both market situations and the negotiator's own requirements. Furthermore, this model allowed agents to deliver multiple offers based on different preferences. By sending these alternative offers, opponents can select their favorite one without sacrificing the negotiator's own profits, so as to increase the utilities of all negotiation parties and the efficiency of the negotiation system.

The rest of this chapter is organized as follows. Section 7.2 proposes the market-based multiple-offer negotiation model, including issues and negotiation environment representations, counter-offer generation, offer evaluation and a negotiation protocol. Section 7.3 illustrates experimental results of the proposed model in different negotiation environments. Section 7.4 concludes this chapter.

## 7.2 Market-Based Model

### 7.2.1 Issue Representation

In most existing multi-issue negotiation models [FWJ04a, BJT04], negotiators' preferences are presented linearly. Although such a linear representation is convenient in modeling and calculation, it is not very suitable to represent humans' concerns

in real world situations. For example, if 1 indicates 100% concern on an item, very few people can really realize how great the difference between 0.6 and 0.7 is when they define concerns on the item. So nonlinear indicators are more suitable to fulfill such a task. In some models [FIK08], nonlinear indicators are adopted to represent negotiators concerns, but the significance on each issue is still fixed and negotiators cannot deliver different preferences. For example, alternative criteria from a car buyer between ‘lower price’ and ‘longer warranty’ cannot be expressed by existing issue representation approaches. In this subsection, we propose a non-linear issue representation to solve this problem. The purpose of the following definitions is to introduce a novel way to represent both the significance of issues and the relationships between issues in multi-issue negotiation, and to express multiple preferences in negotiations.

**Definition 7.1** *A negotiator’s concern on a negotiated issue is represented by a unique concern tag  $\kappa$ ,  $\kappa \in \{S, N, I\}$ , where tag  $S$  indicates a significant issue, tag  $N$  indicates a normal important issue and tag  $I$  indicates an inessential issue. The negotiator may have different negotiation strategies and outcome expectations for issues marked by different concern tags.*

**Definition 7.2** *The relationship between two issues or two AIEs is represented by a unique role tag  $\xi$ ,  $\xi \in \{\cap, \cup\}$ . Tag  $\cap$  indicates a union relationship between parties on two sides, and a negotiator’s expectation on both sides must be satisfied together by the final agreement. Tag  $\cup$  indicates an alternative relationship between parties on two sides, and a negotiator’s expectation on either side must be satisfied by the final agreement.*

**Definition 7.3** *An Atomic Issue Expression (AIE) is a combination of all negotiated issues. Each issue in an AIE must be assigned a unique concern tag. The relationship between issues must be the union relationship and indicated by role tag  $\cap$ . Each AIE indicates one preference of a negotiator.*

**Definition 7.4** *A Complete Issue Expression (CIE) is a combination of AIEs. The relationship between any two AIEs in a CIE must be the alternative relationship and indicated by the role tag  $\cup$ . A CIE indicates all preferences of a negotiator. A negotiator could have multiple preferences, but a satisfaction on any preference will lead negotiators to a final agreement.*

For example, in a three-issue negotiation, if a negotiator's *CIE* is  $(I_1^S \cap I_2^N \cap I_3^I) \cup (I_1^N \cap I_2^S \cap I_3^I)$ , this indicates that the negotiator has two different preferences on negotiated issues. The first *AIE*  $(I_1^S \cap I_2^N \cap I_3^I)$  indicates a preference which has significant concern tag on Issue  $I_1$ , normal concern tag on Issue  $I_2$  and inessential concern tag on Issue  $I_3$ , and the second *AIE*  $(I_1^N \cap I_2^S \cap I_3^I)$  indicates a preference which has normal concern tag on Issue  $I_1$ , significant concern tag on Issue  $I_2$  and inessential concern tag on  $I_3$ . However, a satisfaction on either *AIE* can lead the negotiator to an agreement.

### 7.2.2 Negotiation Environment Representation

Through our studies, we notice that in real-world markets, although people can define reserved offers in advance to represent their expectations, in most cases it is not necessary for them to make their final decisions exactly based on the predefined reserved offers; people may modify their predefined reserved offers. For example, a hesitant buyer may look forward to gaining more profit when he/she notices that his/her expectations can be satisfied easily by most sellers. On the other hand, a rush buyer may accept an offer even if it is worse than his original expectation. However, most existing negotiation approaches do not take these situations into account, and negotiators have to make their final decisions exactly based on the predefined reserved prices. In this subsection, we introduce a market-based negotiation model to consider impacts from environment changes on negotiations, and to help negotiators to make more accurate judgements and wise decisions in e-marketplaces when the status of an e-marketplace changes.

Let  $s$  ( $s \geq 1$ ) denote the number of suppliers,  $c$  ( $c \geq 1$ ) denote the number of consumers,  $\alpha$  denote a negotiator's role (a supplier or a consumer), and  $\beta$  denote the negotiator's attitude on the changes of a negotiation environment. If we employ the relationship between supply and demand to represent a market's situation at a certain moment, then the market's situation can be defined as:

$$\Phi(s, c, \alpha) = \frac{c - s}{c + s} \times \alpha \quad (7.1)$$

where  $\alpha = -1$  for consumers and  $\alpha = 1$  for suppliers.

The range of Equation 7.1 is in-between  $-1$  and  $1$ , and representing the status of a negotiation environment. If  $0 < \Phi < 1$ , the environment is in a beneficial status and the negotiator has an advantage in such an environment. If  $-1 < \Phi < 0$ , the

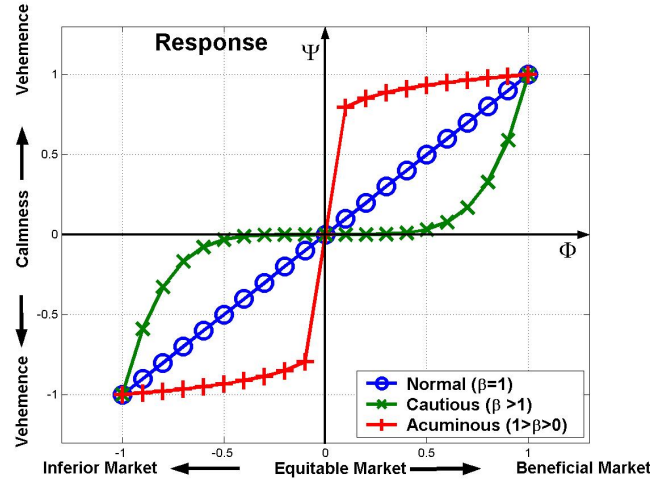


Figure 7.1: Negotiators' responses to markets' situations

environment is in an inferior status and the negotiator has a disadvantage in the environment. If  $\Phi = 0$ , the environment is in an equitable status and the negotiator does not have an advantage or disadvantage in the environment. Objectively, Equation (7.1) represents the relationship between supply and demand in a negotiation environment at a certain moment. However, even for the same situation, negotiators may also have different considerations on environment changes based on their individual situation. Therefore, we generate a graph in Figure 7.1 to map objective negotiation environments to subjective responses of negotiators.

In Figure 7.1, the  $x$ -axis represents situations of a negotiation environment ( $\Phi$ ), and the  $y$ -axis indicates a response from a negotiator ( $\Psi$ ). In general, it can be seen that negotiators may have three typical attitudes to respond to changes in an environment.

1. Cautious ( $\beta > 1$ ): when an environment's status shifts away from equitable to beneficial or inferior, a negotiator's response is very calm when changes of the environment are not significant. However, when changes in the environment are evident, the negotiator's response will become more vehement.
2. Acuminous ( $1 > \beta > 0$ ): when an environment's status shifts away from equitable to beneficial or inferior, a negotiator performs very sensitively even though the change in the environment is not very obvious. However, when the environment's status changes a lot, the negotiator has to control its response for some objective reasons (e.g. the negotiator cannot make further



concession).

3. Normal ( $\beta = 1$ ): when an environment's status shifts away from equitable to beneficial or inferior, a negotiator's response is also shifted from calmness to vehemence gradually.

Even though the above three typical responses cannot cover all possible situations of negotiators' attitudes on market changes, they can still cover most general cases. Based on such a consideration, an agent's response to the negotiation environment can be defined as follows by considering both objective and subjective factors from marketplaces and negotiators, respectively:

$$\Psi(s, c, \alpha, \beta) = \begin{cases} \Phi(s, c, \alpha)^\beta, & \Phi(s, c, \alpha) \geq 0 \\ -[-\Phi(s, c, \alpha)]^\beta, & \Phi(s, c, \alpha) < 0 \end{cases} \quad (7.2)$$

In the following subsections, we introduce a counter-offer generation approach and an offer evaluation approach based on an agent response to a negotiation environment, respectively.

### 7.2.3 Counter-Offer Generation

#### Single Issue

We firstly introduce a counter-offer generation approach on single issue. According to Fatima et al. [FWJ02], a package deal procedure is the optimal procedure in incomplete information settings compared with simultaneous and sequential procedures. In our model, negotiators will adopt the package deal procedure. For Negotiator  $P$ , let vector  $\vec{O}_{t,i} = (o_{t,i}^1, \dots, o_{t,i}^m, \dots, o_{t,i}^M)$  denote an offer  $P$  received from the  $i^{th}$  opponent at round  $t$ , where  $t \leq \tau$  ( $\tau$  is Negotiator  $P$ 's deadline), and  $i \leq A$ , where  $A$  is the total number of Negotiator  $P$ 's opponents,  $M$  indicates the total number of negotiated issues, and  $o_{t,i}^m$  is a particular offer on the  $m^{th}$  issue at round  $t$ . Let matrix  $\mathbf{O}_t = \{\vec{O}_{t,1}, \dots, \vec{O}_{t,i}, \dots, \vec{O}_{t,A}\}^T$  denote offers from all available opponents at round  $t$  and vector  $\vec{O}_t^m = (o_{t,1}^m, \dots, o_{t,i}^m, \dots, o_{t,A}^m)$  denote all offers from all available opponents on the  $m^{th}$  issue at round  $t$ . Let  $o_t^{mb}$  denote the 'best' offer in  $\vec{O}_t^m$ ,  $o_t^{mw}$  denote the 'worst' offer in  $\vec{O}_t^m$ ,  $o_t^{ma}$  denote the average of  $\vec{O}_t^m$  ( $o_t^{ma} = \frac{1}{A} \sum_{i=1}^A o_{t,i}^m$ ),  $o_{t'}^{mb}$  denote the estimated 'best' offer in next round  $t'$ ,  $co_t^m$  denote Negotiator  $P$ 's

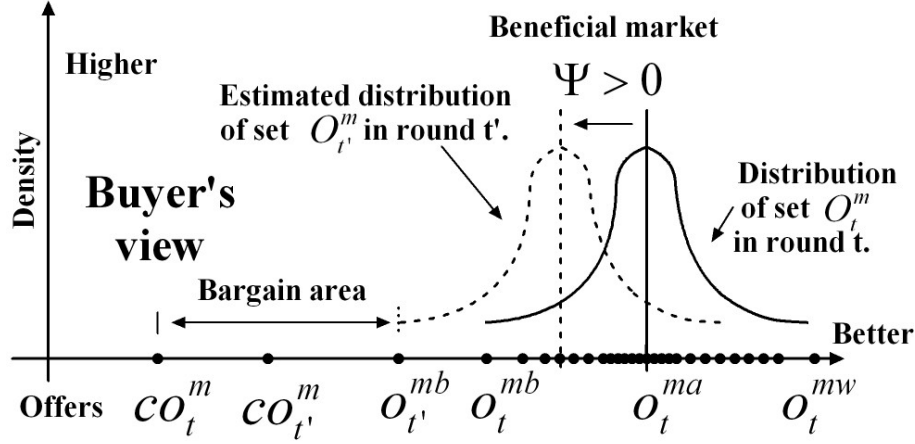


Figure 7.2: Counter-offer generation

last counter-offer on the  $m^{th}$  issue and  $co_{t'}^m$  denote Negotiator  $P$ 's counter-offer for next round on the  $m^{th}$  issue. Suppose Negotiator  $P$  plays as a buyer and the negotiated issue is a car's price, then one possible situation of the counter-offer generation procedure in round  $t$  on the  $m^{th}$  issue as illustrated in Figure 7.2.

In Figure 7.2, the  $x$ -axis indicates offers, and the  $y$ -axis represents the occurrence density of each offer. The solid curve indicates the distribution of  $\vec{O}_t^m$  in round  $t$  (distributions may be different from case to case), and the dotted line is the estimated distribution of  $\vec{O}_{t'}^m$  in the next round. We make the assumption that the shape of the distribution curve of set  $\vec{O}_{t'}^m$  is similar to  $\vec{O}_t^m$ 's, but just the range of span is changed. Because the negotiator plays as a buyer and the negotiated issue is a car's price, so the market represented in Figure 7.2 is a beneficial market ( $\Psi > 0$ ). In a beneficial market, for buyers, opponents' offers on a car's price in next round  $\vec{O}_{t'}^m$  is estimated to be smaller than  $\vec{O}_t^m$  on average. The distance between the current counter-offer  $co_t^m$  and the estimated 'best' offer  $o_{t'}^{mb}$  in next round is the bargaining area. The new counter-offer  $co_{t'}^m$  is generated within this area according to the negotiator's strategies, remaining rounds and importance of issue  $m$ .

Firstly, we estimate the 'best' offer  $o_{t'}^{mb}$  in the next round  $t'$  as follows:

$$o_{t'}^{mb} = o_t^{mb} + \Psi(s, c, \alpha, \beta) \times \sqrt{D(\vec{O}_t^m)} \times \gamma \quad (7.3)$$

$$D(\vec{O}_t^m) = \sum_{i=1}^A (o_{t,i}^m - E(\vec{O}_t^m))^2 p_i \quad (7.4)$$

where  $D(\vec{O}_t^m)$  indicates the variance of  $\vec{O}_t^m$ ,  $\gamma = -1$  for issues in which an agent

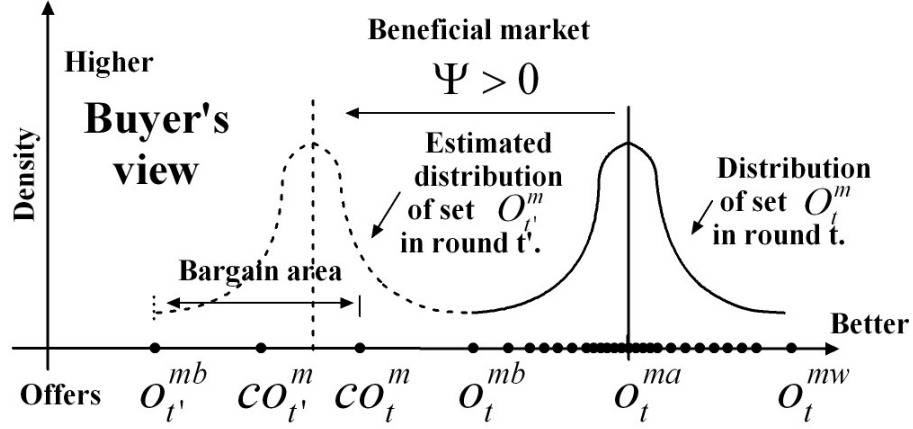


Figure 7.3: Counter-offer generation

prefers a lower value, and  $\gamma = 1$  for issues in which an agent prefers a greater value,  $E(\vec{O}_t^m)$  indicates the mathematical expectation of  $\vec{O}_t^m$ ,  $p_i$  indicates the distribution of  $o_{t,i}^m$  and  $\Psi(s, c, \alpha, \beta)$  indicates the agent's response to the market situation. Usually, when the distribution of  $\vec{O}_t^m$  is a Gaussian distribution, then  $E(\vec{O}_t^m) = o_t^{ma}$ ,  $p_i = \frac{1}{A}$  and Equation 7.4 is specified as:

$$D(\vec{O}_t^m) = \frac{\sum_{i=1}^A (o_{t,i}^m - o_t^{ma})^2}{A} \quad (7.5)$$

Then the new counter-offer  $co_{t'}^m$  for the  $m^{th}$  issue is generated as follows:

$$co_{t'}^m = \begin{cases} o_{ini}^m & t = 0, \\ co_t^m + (o_{t'}^{mb} - co_t^m) \times (\frac{t}{\tau})^\lambda & \kappa(m) = S \text{ and } t \leq \tau, \\ co_t^m + \frac{1}{2}(o_{t'}^{mb} - co_t^m) \times (1 + \frac{t}{\tau})^\lambda & \kappa(m) = N \text{ and } t \leq \tau, \\ o_{t'}^{mb} & \kappa(m) = I \text{ and } t \leq \tau. \end{cases} \quad (7.6)$$

where  $o_{ini}^m$  is the negotiator's initial offer on the  $m^{th}$  issue,  $\kappa(m)$  indicates issue  $m$ 's concern tag, and we simply adopt parameter  $\lambda$  in Faratin et al.'s model [FSJ98] to represent the negotiator's bargaining strategies.

In Figure 7.3, it can be seen that when the market becomes very beneficial to the buyer agent, it is possible that  $o_{t'}^{mb} < co_t^m$  and  $co_{t'}^m < co_t^m$ . So in the market-based negotiation model, we propose a decommitment mechanism which allows negotiators to reject previous offers if these offers are not formally accepted by any opponents. The reason behind such a mechanism is that in the market-based negotiation model, both offer evaluation approach and counter-offer generation approach are impacted by market situations. When the market situation changes, negotiators may change

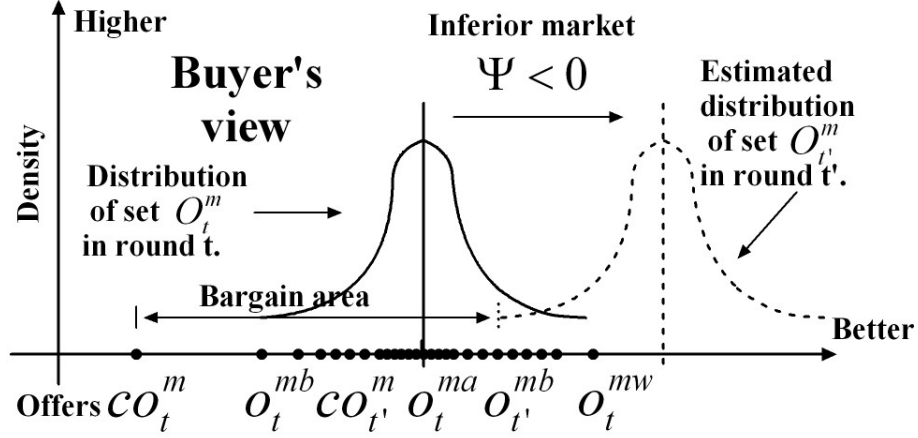


Figure 7.4: Counter-offer generation

their considerations on both the offer evaluations and the counter-offer generations in order to gain more profits. For example, a buyer may generate disadvantageous counter-offers when the market is inferior. However, when the buyer notices that the market may become better, and if the previous counter-offer is not accepted by any seller, then the buyer can reject the previous disadvantageous counter-offers and re-generate advantageous counter-offers in order to increase its profit. On the other hand, if a seller notices that the market may become inferior for him/her in advance, then the seller may accept that buyer's latest offer in order to avoid loss in the future.

Also, markets may become inferior for buyers. In Figure 7.4, it can be seen that when a market is inferior for buyers, the estimated 'best' offer for the following round  $t'$  is worse than the 'best' offer in round  $t$  (i.e.,  $o_{t'}^{mb} > o_t^{mb}$ ). During negotiations, if a new counter-offer in round  $t'$  can bring more profits to a negotiator than the 'best' offer in round  $t$ , then the negotiator will keep on bargaining with opponents and send out the new counter-offer  $co_{t'}^m$ . However, if the new counter-offer is worse than the 'best' offer from opponents, then the negotiator will not send the new counter-offer  $co_{t'}^m$ , but make its final decision based on the comparison result between the 'best' offer ( $o_t^{mb}$ ), the new counter-offer ( $co_{t'}^m$ ), and the negotiator's eagerness to reach an agreement. The eagerness ( $\varepsilon \in [0, 1]$ ) is predefined by the negotiator to indicate its eagerness for completing negotiations (see Subsection 7.2.4 for more detail about eagerness).

### Multi-issue

Based on the single issue counter-offer generation approach, we introduce a counter-offer generation approach for multi-issue negotiation by considering multiple preferences. In this approach, negotiators can provide multiple choices in each negotiation round according to their different preferences. For example, when a prospective car purchaser negotiates with several car dealers on a car's price and warranty, usually dealers will not make great concessions on both price and warranty, and the purchaser may have a consideration such as 'I would like to purchase the car if its price is lower than \$30,000 or if its warranty is longer than 5 years'. In this situation, the purchaser has alternative expectations on negotiation outcomes, but such a situation is not considered by most existing negotiation models. In order to solve this problem, we introduce a multi-issue counter-offer generation approach to deliver negotiators' multiple preferences during negotiations.

In multi-issue negotiation, by assigning concern tags and relationship tags on negotiated issues (see Subsection 7.2.1), a *CIE* can be generated. A negotiator's multiple preferences on multi-issue are indicated by the *CIE*. Therefore, in this multiple-offer approach, the number of offers delivered by the negotiator in each round at one time equals the *AIEs*' number in the *CIE*. Each *AIE* indicates one preference of the negotiator. By employing the counter-offer generation function introduced in the previous subsection on each issue in each *AIE*, multiple offers can be generated based on the *CIE* and delivered to opponents as follows:

$$\Gamma(t, AIE) = C\vec{O}_t = (co_t^1, \dots, co_t^m, \dots, co_t^M) \quad (7.7)$$

$$\Gamma(t, CIE) = \bigcap \Gamma(t, AIE), \forall AIE \in CIE \quad (7.8)$$

where each  $co_t^m$  in each *AIE* is calculated by adopting Equation 7.6.  $\Gamma(t, AIE)$  indicates an counter-offer based on the preference implied by an *AIE*, and  $\Gamma(t, CIE)$  indicates all counter-offers based on multiple preferences implied by all *AIEs* in a *CIE*.

### 7.2.4 Offer Evaluation

When negotiators receive offers from opponents, negotiators should make a response based on the evaluation result on offers. In this section, we introduce an offer evaluation approach to consider both outcome expectations of negotiators and negotiation environments. In a dynamic situation, an offer evaluation result may also be impacted by a change of the negotiation environment. For example, if a car's real value can be evaluated correctly by buyers in an equitable market, then the car should be overvalued in a seller's market and undervalued in a buyer's market. Based on such a consideration, we propose an offer evaluation approach sensitive to the negotiation environments as follows.

#### Single Issue

Let  $\vec{O}_{t,i} = (o_{t,i}^1, \dots, o_{t,i}^m, \dots, o_{t,i}^M)$  represent a given vector offer from the  $i^{th}$  opponent at round  $t$ , where  $o_{t,i}^m$  denotes the offer on the  $m^{th}$  issue. Let  $\vec{O}_{ini} = (o_{ini}^1, \dots, o_{ini}^m, \dots, o_{ini}^M)$  denote Negotiator  $P$ 's initial offer vector. Then, without considering the market situation, each single offer  $o_{t,i}^m$  in vector  $\vec{O}_{t,i}$  is evaluated by Negotiator  $P$  as follows.

$$\Lambda(o_{t,i}^m, o_{ini}^m, \gamma) = \mathbf{th} \left( \frac{o_{t,i}^m - o_{ini}^m}{o_{ini}^m} \times \gamma \right) + 1 \quad (7.9)$$

where  $\gamma = -1$  for issues in which an agent prefers a lower value, such as a buyer prefers a lower price on a car; and  $\gamma = 1$  for issues in which an agent prefers a greater value, such as a buyer prefers a longer warranty on a car.  $\mathbf{th}(x)$  is defined as follows.

$$\mathbf{th}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (7.10)$$

The result of Equation 7.9 ( $\Lambda \in (0, 2)$ ) indicates how Negotiator  $P$ 's initial offer is satisfied by the offer  $o_{t,i}^m$ . For example, assume Negotiator  $P$  plays as a consumer and wants to evaluate a price offer. Because a lower price is better for Negotiator  $P$ , so  $\gamma = -1$ . For a given price offer  $o_{t,i}^m$ , when  $o_{t,i}^m = o_{ini}^m$  then  $\Lambda = 1$ . This means that the consumer's expectation is satisfied. When  $o_{t,i}^m > o_{ini}^m$  then  $0 < \Lambda < 1$ , which indicates that the consumer's expectation is only partially achieved. And when  $o_{t,i}^m \leq o_{ini}^m$  then  $1 < \Lambda < 2$ , which implies that the consumer's expectation is overachieved.

Because Equation (7.9) only evaluates the offer  $o_{t,i}^m$  based on Negotiator  $P$ 's initial

offer but does not take the situation of the negotiation environment into account, so the evaluation results may not be accurate enough to reflect the value of the given offer in a particular market. Therefore, by considering market situations, negotiators can get a more accurate evaluation result on the offer  $o_{t,i}^m$  as follows:

$$\Theta(o_{t,i}^m, s, c, o_{ini}^m, \alpha, \beta, \gamma) = \frac{\Lambda(o_{t,i}^m, o_{ini}^m, \gamma)}{\Psi(s, c, \alpha, \beta) + 1} \quad (7.11)$$

The result of Equation 7.11 ( $\Theta \in (0, 1)$ ) indicates the negotiator's utility by accepting the offer  $o_{t,i}^m$  in a certain market. If it is an equitable market ( $\Psi = 0$  and  $\Theta = \Lambda$ ), then the offer  $o_{t,i}^m$  is evaluated unbiasedly. If it is in a beneficial market ( $0 < \Psi < 1$  and  $\Theta < \Lambda$ ), then the offer  $o_{t,i}^m$  is undervalued. And if it is in an inferior market ( $-1 < \Psi < 0$  and  $\Theta > \Lambda$ ), then the offer  $o_{t,i}^m$  is overvalued.

### Multi-Issue

In our model, since negotiators' preferences are represented by concern tags, the traditional approach for multi-issue utility calculation is not applicable anymore. We introduce a non-linear utility calculation approach which takes concern tags into account. For the offer vector  $\vec{O}_{t,i}$ , Negotiator  $P$  generates the combined evaluation result by considering concern tags in a *AIE* as follows:

$$\Upsilon(\vec{O}_{t,i}, AIE) = \min \left( \Theta(o_{t,i}^m) | m \in [1, M], o_{t,i}^m \in \vec{O}_{t,i}, \kappa(m) = \kappa(AIE) \right) \quad (7.12)$$

where  $\Theta(o_{t,i}^m)$  is a simplification of Equation (7.11), and *AIE* indicates one of Negotiator  $P$ 's preferences,  $\kappa(m)$  is the concern tag of the  $m^{th}$  issue in the *AIE*, and  $\kappa(AIE)$  is the highest significant concern tag in the *AIE*. If Negotiator  $P$  has multiple preferences on negotiated issues (i.e. more than one *AIE* in a *CIE*), then Negotiator  $P$ 's final evaluation result by considering all preferences in the *CIE* is calculated as:

$$\Upsilon(\vec{O}_{t,i}, CIE) = \max \left( \Upsilon(\vec{O}_{t,i}, AIE), AIE \in CIE \right) \quad (7.13)$$

It can be seen that in the offer evaluation approach (see Equation 7.9), the reserved offer, which is employed by most negotiation models, is no longer adopted. That is because in dynamic negotiation environments, when the situation of the environment changes, the predefined reserved offer may not be applicable anymore. Instead we use a parameter eagerness ( $\varepsilon \in [0, 1]$ ) to express negotiators' eagerness on completing the negotiation. When  $\varepsilon = 1$ , the negotiator would like to accept

any offer finally in order to complete the negotiation; when  $\varepsilon = 0$ , the negotiator will reject all offers which are worse than the initial offer; when  $0 < \varepsilon < 1$ , the negotiator can only accept the offer  $\vec{O}_{t,i}$  if  $\Upsilon(\vec{O}_{t,i}, CIE) \geq 1 - \varepsilon$ . Therefore, when the market situation changes, negotiators can adjust their evaluations on opponents' offers based on market situations in order to have a more accurate and reasonable reaction.

### 7.2.5 Protocol and Equilibrium

In this subsection, a negotiation protocol for the market-based multi-issue negotiation model is proposed based on Rubinstein's alternating offers protocol [FSJ98].

**Step 1** A negotiator assigns negotiation parameters, i.e., initial offer ( $\vec{O}_{ini}$ , including concerns tags and role tags), eagerness ( $\varepsilon$ ), negotiation deadline ( $\tau$ ), role in negotiation ( $\alpha$ ), attitude on the environment changing ( $\beta$ ), attitude on issues' value ( $\gamma$ ) and bargaining strategy ( $\lambda$ ). The number of consumers ( $c$ ) and suppliers ( $s$ ) can be obtained from the marketplace directly. A  $CIE$  is generated based on the negotiator's preference/s. The negotiator initializes  $t$  to 0 and counter-offer/s  $\Gamma(t, CIE)$  to  $o_{ini}$ .

**Step 2** The negotiator broadcasts counter-offer/s  $\Gamma(t, CIE)$  to all opponents and waits for responses.

**Step 3** Once the negotiator gets responses, if any opponent accepts any offer in counter-offer/s  $\Gamma(t, CIE)$ , then the negotiation is completed. Otherwise, if  $t > \tau$ , the procedure goes to **Step 4**. If  $t \leq \tau$ , the procedure goes to **Step 5**.

**Step 4** The negotiator has to make the final decision on opponents' offers. For all offers  $\vec{O}_t$  from all opponents at round  $t$ , let  $\vec{O}_t^b$  denote the offer which brings greatest profit to the negotiator. If  $\Upsilon(\vec{O}_t^b, CIE) \geq 1 - \varepsilon$ , the negotiator accepts  $\vec{O}_t^b$  and the negotiation is completed. Otherwise, the negotiation fails.

**Step 5** The negotiator will generate new counter-offer/s  $\Gamma(t, CIE)$  for the next round. Let  $\Upsilon(\Gamma(t, CIE), CIE)$  denote the utility that the negotiator may gain from the counter-offer/s  $\Gamma(t, CIE)$ . If  $\Upsilon(\vec{O}_t^b, CIE)$  is greater than both  $\Upsilon(\Gamma(t, CIE), CIE)$  and  $1 - \varepsilon$ , then  $\vec{O}_t^b$  is accepted by the negotiator and the negotiation is completed. If  $1 - \varepsilon$  is greater than both  $\Upsilon(\vec{O}_t^b, CIE)$  and



$\Upsilon(\Gamma(t, CIE), CIE)$ , then the negotiator leaves off the procedure and the negotiation fails. If  $\Upsilon(\Gamma(t, CIE), CIE)$  is greater than both  $\Upsilon(\vec{O}_t^b, CIE)$  and  $1 - \varepsilon$ , then the procedure goes to **Step 6**.

**Step 6** The negotiator updates  $t$  to  $t'$  ( $t' = t + 1$ ),  $\Gamma(t, CIE)$  to  $\Gamma(t', CIE)$ , parameters  $c$ , and  $s$  according to the current market situation and parameter  $\varepsilon$ , and the procedure goes back to **Step 2**.

Based on the above procedure, the negotiator's equilibrium in round  $t$  is defined as follows :

$$\Omega(t) = \begin{cases} \textbf{Quit}, \text{ when } t \geq \tau \wedge \Upsilon(\vec{O}_t^b, CIE) \geq 1 - \varepsilon \text{ or } t < \tau \wedge \\ \max(\Upsilon(\vec{O}_t^b, CIE), \Upsilon(\Gamma(t, CIE), CIE), 1 - \varepsilon) = 1 - \varepsilon, \\ \\ \textbf{Accept } \vec{O}_t^b, \text{ when } t \geq \tau \wedge \Upsilon(\vec{O}_t^b, CIE) \geq 1 - \varepsilon \text{ or } \\ t < \tau \wedge \max(\Upsilon(\vec{O}_t^b, CIE), \Upsilon(\Gamma(t, CIE), CIE), 1 - \varepsilon) = \Upsilon(\vec{O}_t^b, CIE), \\ \\ \textbf{Offer } \Gamma(t, CIE), \text{ when } t < \tau \wedge \\ \max(\Upsilon(\vec{O}_t^b, CIE), \Upsilon(\Gamma(t, CIE), CIE), 1 - \varepsilon) = \Upsilon(\Gamma(t, CIE), CIE). \end{cases} \quad (7.14)$$

## 7.3 Experiment

The experiment includes six agents, three of them are consumers and the other three are suppliers. The two negotiated issues are a car's price and warranty. Two consumers employ the proposed market-based model, and the others employ the commonly used NDF model [FSJ98]. All agents employ the package deal procedure and each offer is delivered in the form of (*dollar, year*). All settings about agents and the negotiation environment are displayed in Table 7.1. In the first scenario, three buyer agents, (Agents *db1*, *db2* and *nb1*) and two seller agents, (Agents *nb1* and *nb2*) participate in the negotiation. Based on the negotiation environment of Scenario 1, one seller agent (Agent *nb3*) will join the negotiation in the second scenario and one seller agent (Agent *nb2*) will leave off the negotiation in the third scenario, respectively. Figures 7.5 to 7.7 show how the proposed market-based model captures the changes of the negotiation environment, and offers in each negotiation

Agent role	Consumer			Supplier		
Agent name	db1	db2	nb1	ns1	ns2	ns3
Negotiation model	Market-based model			NDF model		
Initial offer	(\$2000, 5y)			(\$3000, 2y)	(\$2700, 1.8y)	(\$3300, 2.2y)
Reserved offer	eagerness=1			(\$3000, 2y)	(\$2000, 5y)	(\$1800, 4.5y)
Preference	$(d^S \cap y^S)$	$(d^S \cap y^N) \cup (d^N \cap y^S)$		(0.5, 0.5)		

Table 7.1: Experiment setup

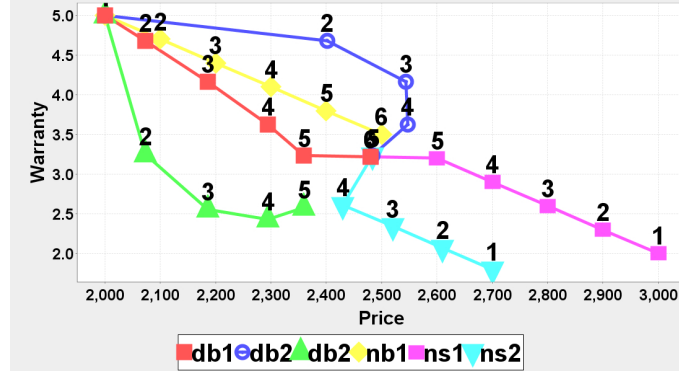


Figure 7.5: Negotiation in an equitable market.

round are highlighted by index number. Agent *db1* employs the market-based model and its *CIE* is  $(d^S \cap y^S)$ . Agent *db2* employs the market-based model as well and its *CIE* is  $(d^S \cap y^N) \cup (d^N \cap y^S)$ . Agent *db2* delivers two offers in each negotiation round. Finally, in order to fairly evaluate the performance of different negotiation approaches, their agreements are compared based on the Euclidean distance to the initial offer (\$2000, 2y).

In the first scenario, because the consumer's number is greater than the supplier's number, the market status is inferior for consumers. In Figure 7.5, it can be seen that

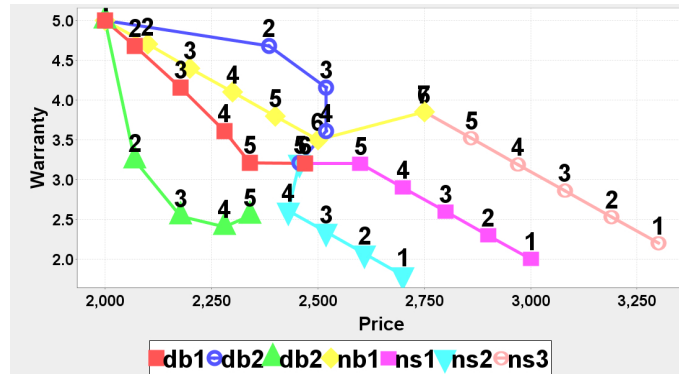


Figure 7.6: Negotiation in a beneficial market.

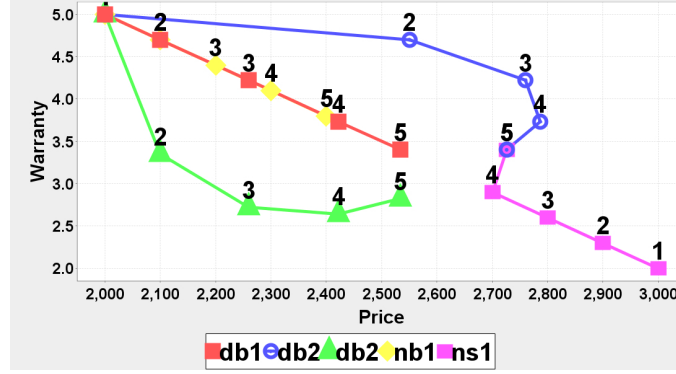


Figure 7.7: Negotiation in a inferior market.

Agent *db2* delivers two offers in each round and sellers can pick up either one based on their individual preferences. Because Agent *db2* provides more options to its opponents, Agent *db2* reaches an agreement firstly with Agent *ns2* at (\$2484, 3.2y). Since Agent *db1* does not provide alternative offers to opponents, offers delivered by Agent *db1* are located between Agent *db2*'s paratactic offers. In round-6, Agent *db1* achieves an agreement secondly with Agent *ns1* at (\$2480, 3.2y). By comparing these two agreements, it can be seen that Agent *db2* gets a little bit more profit than Agent *db1* in a shorter time. In this scenario, Agent *nb1* does not reach an agreement with any seller agents and fails the negotiation.

In the second scenario, because the consumer's number equals the supplier's number, the market is in equitable status for all negotiators. In Figure 7.6, when seller Agent *ns3* enters into the negotiation, the environment becomes better for buyers than the first scenario. Agent *db2* reaches an agreement firstly with Agent *ns3* at (\$2457, 3.2y) and agent *db1* achieves an agreement secondly with Agent *ns1* at (\$2470, 3.2y). By comparison with the first scenario, it can be seen that both market-based buyer agents gain more profits as the environment improves. The NDF Agent *nb1* reaches an agreement with Agent *ns2* finally at (\$2750, 3.8y). Obviously, Agents *db2* and *db1*'s outcomes are much better than Agent *nb1*'s, based on the consideration of Euclidean distance to the initial offer (\$2000, 2y). Also, it can be confirmed that the agent which provides multiple options to opponents can gain more profits in multilateral negotiations.

In the third scenario (Figure 7.7), it can be seen that when seller Agent *ns2* leaves off the negotiation, the negotiation environment becomes more disadvantageous for buyer agents (i.e. more competitive). Finally, buyer Agent *db2* won the negotiation with the only seller Agent *ns1* at (\$2726, 3.4y). Even though this agreement is worse

than the previous two scenarios for Agent *db2*, Agent *db2* defeats other buyer agents and reaches agreement with the only seller agent. Therefore, we can say that the market-based agent can win the negotiation in competition and the multiple offer strategy increases the chance for it to be the winner.

In Figure 7.8, we illustrate a model to demonstrate how environments and agents' eagerness impact agents' strategies and decisions in negotiations. The  $x$ -axis denotes negotiation environments (refer to Equation (7.1)), the  $y$ -axis denotes agents' eagerness for completing negotiations, and the  $z$ -axis denotes agents' evaluation results on offers (refer to Equation (7.9)). Then by setting all negotiation parameters ( $\beta$  and  $\lambda$ ) to 1, a trading surface for the market-based negotiation model can be formulated as follows.

$$\Lambda(\Phi, \varepsilon) = \begin{cases} (1 + \Phi) * (1 - \varepsilon), & \text{when } -1 \leq \Phi \leq 0, \\ (\Phi - 1) * \varepsilon + 1, & \text{when } 0 < \Phi \leq 1. \end{cases} \quad (7.15)$$

where  $\varepsilon \in [0, 1]$  and  $\Phi \in [-1, 1]$ .

The trading surface defines a set of thresholds on agents' profits. During a negotiation, agents will accept offers above or on the surface, but reject offers below the surface. Also, we display another trading surface for the NDF model. Comparison with the market-based model, the trading surface of the NDF model is just a plane surface. That means agents in the NDF model fix their thresholds in all situations as a constant, and do not consider changes of the environment and eagerness of completion of negotiations.

In this section, we illustrated experimental results in different negotiation environments and also compared outcomes between the market-based model and the NDF model. Based on these results, we can claim that the market-based agents can modify their negotiation strategies dynamically when the negotiation environment changes. Also, the multiple offer strategy increases the probability for agents to enlarge their outcome profits and/or to enlarge their chances to win negotiation. Therefore, the market-based multiple offer model can help agents to make wiser decisions in complex negotiation environments.

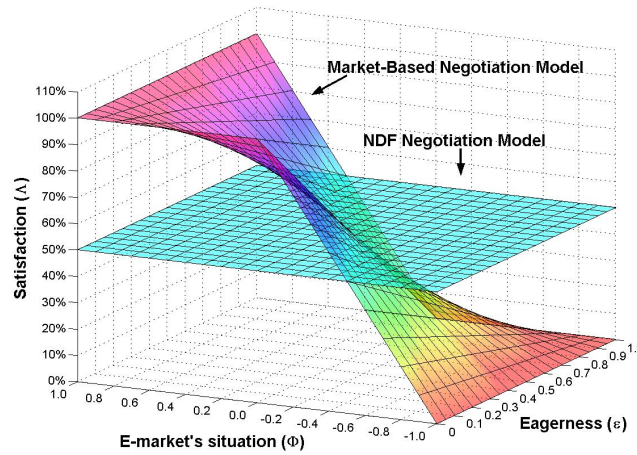


Figure 7.8: Trading surface of negotiation models.

## 7.4 Summary

This chapter presented a market-based multiple-offer negotiation model to help agents to make wise decisions in multilateral, multi-issue negotiation. In our model, the offer evaluation approach and counter-offer generation approach have taken the negotiation environment into account. Offers from opponents are evaluated relatively by considering the negotiation environment and agents' eagerness for trading. Based on experimental results, we further put forward the concept of 'trading surface' and discovered that the trading surface of the market-based negotiation model is more applicable than the NDF model's in complex e-marketplaces.

# Chapter 8

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## Multiple Related Negotiations

In the previous three chapters 5 to 7, three approaches to solve three research issues in multilateral negotiation (on the second level of our proposed hierarchical negotiation model) were proposed, namely negotiation partner selection, multilateral single issue negotiation, and multilateral multi-issue negotiation. This chapter investigates and introduces our solution to solve some research issues in multiple related negotiation (the third level of the hierarchical negotiation model).

### 8.1 Introduction

In complex negotiation environments, one agent may perform more than one negotiation with different opponents for different goals at the same time. Sometimes, these goals are not independent, and these multiple negotiations are somehow related. For instance, in a scheduling problem, the negotiation result on the deadline of an early occurring event will definitely impact the negotiation on the starting time of a later occurring event. The negotiation result between a mortgagor and a banker on a mortgage will determine the mortgagor's reservation in the negotiation with a real estate agent on a property's price.

According to our studies, significant achievements have been reached in agent negotiation in the first two levels (bilateral negotiation level and multilateral negotiation level) with state-of-the-art techniques and approaches [FWJ04a, FWJ06a, FWJ09, HSLM07]. However, very few of them consider the third level and can handle multiple related negotiation properly [HRLJ06, PT09, ZL07]. Most existing approaches just separate these related negotiations and treat each of them individually. The major disadvantage of dealing with those negotiations separately is that if related negotiations are not considered together, the negotiation outcomes may not be optimized and may even be damaged in some cases. For instance, if a doctor

schedules one patient's booking without considering other bookings, his schedules will be inefficient or conflicting. If a mortgagor does not take the possible negotiation result with a banker into account during the negotiation with a real estate agent, she may not successfully borrow sufficient money to purchase a property, or may borrow more money than the requested amount and has to pay unnecessary interest.

In order to solve the problem mentioned above in multiple related negotiation, we introduce a Multi-Negotiation Network (MNN) and a Multi-Negotiation Influence Diagram (MNID) in this chapter. Firstly, multiple related negotiation are represented by a MNN. Secondly, the MNN is extended to a MNID. The joint success rate and the joint utility by considering all related negotiations in the MNID is calculated. Thirdly, an optimal policy to conduct multiple related negotiation is calculated for the MNID, by considering both the joint success rate and the joint utility, to optimize the negotiation outcome of multiple related negotiation in the MNID.

The chapter is organized as follows. In Section 8.2, a Multi-Negotiation Network is proposed to handle multiple related negotiation. In Section 8.3, a Multi-Negotiation Influence Diagram is introduced to solve the decision problem in a MNN. In Section 8.4, experiments are demonstrated in two scenarios to illustrate the performance of the proposed approach. Section 8.5 concludes this chapter.

## 8.2 A Multi-Negotiation Network

### 8.2.1 Construction of A MNN

In this subsection, we introduce notations for a MNN and the procedure to construct a MNN based on Bayesian Networks [JN01]. Let a four-tuple  $\langle \mathbb{G}, \mathbf{R}, \mathbf{P}, \Phi \rangle$  indicate a MNN, where  $\mathbb{G} = (\mathbf{V}, \mathbf{E})$  is a directed acyclic graph, set  $\mathbf{R}$  indicates the restriction function between two related negotiations,  $\mathbf{P}$  is a set of success rates, and  $\Phi$  is a set of utility functions.  $\mathbf{V}$  is a finite, nonempty set of vertices and each vertex indicates a negotiation in a MNN.  $\mathbf{E}$  is a set of ordered pairs of distinct elements of  $\mathbf{V}$ . Each element of  $\mathbf{E}$  is called a restriction edge with a direction to represent a dependency relationship of two related negotiations, (i.e. a link with an arrow between two vertices in a MNN). For example, if a pair  $(V_i, V_j) \in \mathbf{E}$ , we say that there is an edge from  $V_i$  to  $V_j$ . In other words,  $V_j$  depends on  $V_i$ , and

$V_i$  is one of  $V_j$ 's parents. We use function  $r_{ij} : \Phi_j \rightarrow \Phi_j$  ( $r_{ij} \in \mathbf{R}$ ,  $\Phi_j \in \Phi$ ) to indicate the restriction between  $V_i$  and  $V_j$ . If there is no restriction between  $V_i$  and  $V_j$ ,  $r_{ij}$  is *nil*. (That means two negotiations  $V_i$  and  $V_j$  are independent and there is no impact on each other.)  $p_i$  ( $p_i \in \mathbf{P}$ ,  $p_i \in [0, 1]$ ) indicates the success rate of  $V_i$  and  $p_i = P(V_i|pa(V_i))$ , where  $pa(V_i)$  are the parents of  $V_i$ .  $\Phi_i$  ( $\Phi_i \in \Phi$ ) indicates the utility function of Negotiation  $V_i$ . Figure 8.1 is an example of a MNN. In this example, the set of vertices in the MNN is  $\mathbf{V} = \{X, Y, Z, W\}$ , the set of edges is  $\mathbf{E} = \{(X, Y), (X, Z), (Y, Z), (Y, W), (Z, W)\}$ , the set of restriction functions is  $\mathbf{R} = \{r_{xy}, r_{xz}, r_{yz}, r_{yw}, r_{zw}\}$ , the set of probabilities is  $\mathbf{P} = \{P(X), P(Y|X), P(Z|X, Y), P(W|Y, Z)\}$ , and the set of utility functions is  $\Phi = \{\Phi_x, \Phi_y, \Phi_z, \Phi_w\}$ .

From a MNN, an agent can view its related negotiations based on dependency relationships of these negotiations. The basic procedure to construct a MNN includes the following three steps.

**Step 1** to represent each negotiation by a unique vertex  $V_i$  ( $V_i \in \mathbf{V}$ ) and to assign a utility function  $\Phi_i$  ( $\Phi_i \in \Phi$ ) for  $V_i$ . Of course, the agent can modify the utility function anytime;

**Step 2** to generate all restriction edges, which belong to  $\mathbf{E}$ , between each two related negotiations; and to define restriction functions  $\mathbf{R}$  in the form of  $r_{ij} : \Phi_j \rightarrow \Phi_j$  ( $r_{ij} \in \mathbf{R}$ );

The restriction function indicates how an ongoing or accomplished negotiation impacts another ongoing negotiation. An accomplished negotiation will not be impacted by other negotiations anymore. For instance, if a buyer synchronously performs two negotiations between a banker and a real estate agent under the condition that the buyer's reservation on a property's price depends on the mortgage, then there is a restriction edge from the *mortgage negotiation* to the *property negotiation*, and the restriction between these two negotiations can be described as 'the buyer's reservation on a property's price depends on the banker's latest offer in mortgage negotiation'. If the negotiation between the buyer and the banker is completed first, its impact on the negotiation between the buyer and the real estate agent will be fixed. However, if the negotiation between the buyer and the real estate agent is completed first, the *mortgage negotiation* will not have any further impact on the *property negotiation*. In a MNN, if Negotiation  $V_i$  is an independent negotiation, other



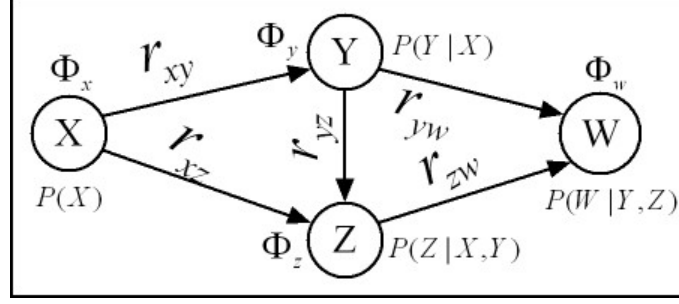


Figure 8.1: A Multi-Negotiation Network.

negotiations will have no impact on its utility function  $\Phi_i$ . Otherwise, if Negotiation  $V_i$  has  $K$  dependent negotiations, then its utility function will be modified by the consideration of all impacts from these  $K$  dependent negotiations as follows:

$$r_{1i} \circ \dots \circ r_{Ki} : \Phi_i \rightarrow \Phi_i \quad (8.1)$$

Taking the MNN in Figure 8.1 as an example. Negotiation  $X$  has no dependent negotiations, its utility function does not need modification; Negotiation  $Y$  is dependent on Negotiation  $X$ , its utility function is modified as  $\Phi_y = r_{xy}(\Phi_y)$ ; Negotiation  $Z$  is dependent on Negotiations  $X$  and  $Y$ , its utility function is modified as  $\Phi_z = r_{xz}(r_{yz}(\Phi_z))$ ; and Negotiation  $W$  is dependent on Negotiation  $Y$  and  $Z$ , its utility function is modified as  $\Phi_w = r_{yw}(r_{zw}(\Phi_w))$ .

**Step 3** to define the success rate  $p_i$  ( $p_i \in \mathbf{P}$ ) for Negotiation  $V_i$ .

The success rate  $p_i$  indicates how likely an agent's latest offer will be accepted by its opponents in the remaining negotiation rounds. Suppose in negotiation round  $t$ , the agent's latest offer is represented as a utility vector  $(\Phi_i(t), \Phi_i(t)^o)$ , and one of its opponents' offers is a utility vector  $(u_o^t, u_a^t)$ . The agent's latest offer generates a payoff of  $\Phi_i(t)$  for itself and  $\Phi_i(t)^o$  for its opponents; and the opponent's offer generates a payoff of  $u_o^t$  for itself and  $u_a^t$  for the agent. Let  $u_w$  denote the worst possible utility, (a *conflict utility*) for the agent. If the subjective probability of the agent obtaining  $u_w$  is  $p_w$ , we have:

$$[(1 - p_w)\Phi_i(t) + p_w u_w] \leq u_a \quad (8.2)$$

According to the above inequality, the highest conflict probability that the

agent may encounter with the opponent in the next negotiation round is the maximum value of  $p_w$ :

$$p_w = \frac{\Phi_i(t) - u_a}{\Phi_i(t) - u_w} \quad (8.3)$$

Equation 8.3 indicates the conflict probability that the agent may encounter in the following negotiation round. Let  $\tau$  be the negotiation deadline and  $t$  be the current round, then the conflict probability that the agent may encounter with the opponent by considering all remaining rounds can be estimated as follows:

$$p_w = \left( \frac{\Phi_i(t) - u_a}{\Phi_i(t) - u_w} \right)^{\tau-t} \quad (8.4)$$

Consequently, the aggregated conflict probability that the agent may encounter before the deadline by considering all opponents in Negotiation  $V_i$  is:

$$p_a = \left( \frac{\prod_{s=1}^{S_i} (\Phi_i(t) - u_s)}{(\Phi_i(t) - u_w)^{S_i}} \right)^{\tau-t} \quad (8.5)$$

where  $S_i$  is the number of opponents in Negotiation  $V_i$ . Therefore, for Negotiation  $V_i$ , the success rate  $p_i$  that the agent's offer  $\Phi_i(t)$  will be accepted by at least one opponent before the deadline is:

$$p_i = 1 - p_a = 1 - \left( \frac{\prod_{s=1}^{S_i} (\Phi_i(t) - u_s)}{(\Phi_i(t) - u_w)^{S_i}} \right)^{\tau-t} \quad (8.6)$$

A MNN can be dynamically modified according to changes of the negotiation environment. In the following subsections, we will explain how to dynamically update a MNN.

### 8.2.2 Updating of a MNN

Since negotiation environments can be highly complex and dynamic in real-world situations, agents may need some modifications on their multiple related negotiation in order to respond to changes in negotiation environments. Such modifications may include the following cases: starting a new negotiation, terminating an ongoing negotiation, adjusting utility functions, adjusting restriction functions, changing

negotiation opponents etc. When these changes happen, agents should immediately update their MNNs. In this subsection, we introduce two major operations and suggest other operations incorporating several major changes on MNN updating.

### Starting a Negotiation

Assume that there are  $i$  related negotiations. If a new negotiation is commenced by an agent, a vertex  $V_{i+1}$  should be inserted into the MNN to indicate the new negotiation. Also, the agent should define a utility function  $\Phi_{i+1}$  for Negotiation  $V_{i+1}$ , and specify restriction edges between all existing negotiations and Negotiation  $V_{i+1}$ . If there is a restriction edge from an existing Negotiation  $V_i$  to the new Negotiation  $V_{i+1}$ , restriction functions  $r_{i(i+1)}$  should be specified, and the utility function  $\Phi_{i+1}$  should be modified according to this restriction. If there is a restriction edge from the new Negotiation  $V_{i+1}$  to an existing Negotiation  $V_i$ , then Negotiation  $V_i$ 's success rate  $p_i$  and utility function  $\Phi_i$  should also be updated. In Figure 8.2(a), an example of adding new Negotiation  $Z$  in a MNN is demonstrated.

### Terminating a Negotiation

If an ongoing Negotiation  $V_i$  is terminated by an agent, no matter whether Negotiation  $V_i$  would be successful or fail to reach an agreement, we use lower case letters on Negotiation  $V_i$ 's caption to indicate that the negotiation is in a final state. Meanwhile, the success rate for Negotiation  $V_i$  is set to 1 for a successful negotiation or to 0 for a failed negotiation. For any Negotiation  $V_j$  which Negotiation  $V_i$  depends on, the restriction function  $r_{ji}$  is set to *nil* and Negotiation  $V_i$ 's utility function  $\Phi_i$  is replaced by a constant to indicate the payoff of Negotiation  $V_i$ . For any Negotiation  $V_k$  which depends on Negotiation  $V_i$ , the restriction function  $r_{ik}$  is eventually fixed and its impact on Negotiation  $V_k$ 's utility function is also fixed. In Figure 8.2(b), an example of terminating an ongoing Negotiation  $Z$  in a MNN is demonstrated.

### Other Operations

Besides the previous two situations, agents may modify some ongoing negotiations without adding or deleting negotiation. For example, an agent may modify its negotiation strategy for a negotiation when the number of opponents in the negotiation is changed. An agent can modify its utility function according to its new expectation on negotiation outcome. An agent may delete an existing restriction between two

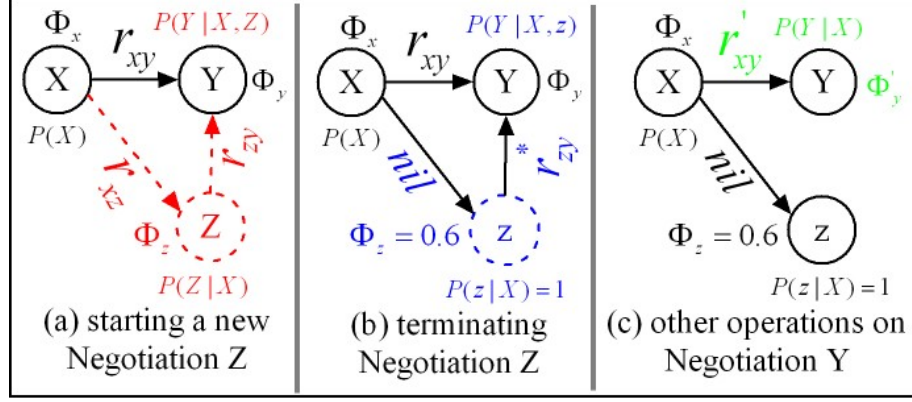


Figure 8.2: Multi-Negotiation Network update.

related negotiations or generate a new restriction between two independent negotiations. In Figure 8.2(c), an example of these operations in a MNN is demonstrated.

### 8.3 Decision Making in a MNN

Because a MNN may contain more than one negotiations, and these negotiation are processed concurrently, whether to accept or reject an offer or even quit from an ongoing negotiation involves a decision making process during negotiations. An agent's decision on a single negotiation may impact its other negotiations or even the whole MNN. This section introduces an efficient procedure which can help agents to make advisable decisions for each negotiation in a MNN in order to optimize the outcome of the MNN by considering both joint utility and success rate.

#### 8.3.1 Multi-Negotiation Influence Diagram

Suppose there are  $I$  negotiations in a MNN  $= \langle \mathbb{G}, \mathbf{R}, \mathbf{P}, \Phi \rangle$ . The decision problem in the MNN is how to make an advisable decision policy for all related negotiations in order to optimize the outcome of the MNN. A decision policy is a set of decisions that the agent makes for all negotiations in a MNN. In general, agents could have three typical decisions on an ongoing negotiation, there being (1) to *accept* the best offer from opponents, (2) to *reject* all offers and send a counter-offer and (3) to *quit* the negotiation. If a MNN contains  $I$  negotiations, the number of total decision policies for the MNN is  $I^3$ , and each policy will generate different outcomes for the MNN. In order to model the relationships between decision policies and corresponding global outcomes, we propose a Multi-Negotiation Influence Diagram (MNID).

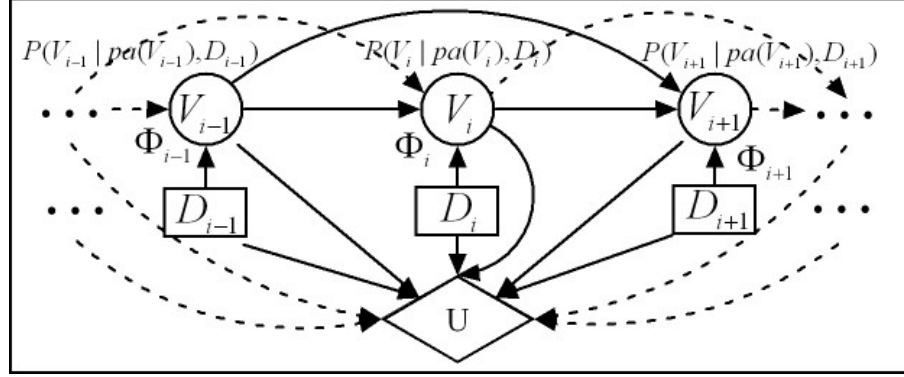


Figure 8.3: A Multi-Negotiation Influence Diagram.

A MNID can be defined by a six-tuple  $\langle \mathbb{G}, \mathbf{R}, \mathbf{P}, \mathbf{\Phi}, \mathbf{D}, U \rangle$ , where  $\mathbb{G}$ ,  $\mathbf{R}$ ,  $\mathbf{P}$ ,  $\mathbf{\Phi}$  are the same as in a MNN, set  $\mathbf{D}$  indicates decisions on each negotiation and  $U$  indicates the joint utility of the MNID by considering all related negotiations.  $D_i = \{a, r, q\}$  ( $D_i \in \mathbf{D}$ ) indicates three possible decisions for Negotiation  $V_i$ , where  $a$  indicates *accept*,  $r$  indicates *reject*, and  $q$  indicates *quit*. A MNN can be extended to a MNID by adding a rectangular node  $D_i$  for each Negotiation  $V_i$  and one diamond node  $U$  for the whole MNN. The edge from each Decision  $D_i$  to the corresponding Negotiation  $V_i$  are added, and all edges from Decision  $D_i$  and Negotiation  $V_i$  to node  $U$  are added as well. In Figure 8.3, a MNID is illustrated. Let  $u(\mathbf{D})$  be the joint utility of the MNID based on decisions  $\mathbf{D}$ , and  $p(\mathbf{D})$  indicates the joint success rate, and  $EU(\mathbf{D})$  indicates the expected utility, then

$$u(\mathbf{D}) = \sum_{i=1}^I u_i(D_i) \times w_i \quad (8.7)$$

$$p(\mathbf{D}) = \prod_{i=1}^I P(V_i | pa(V_i), D_i) \quad (8.8)$$

$$EU(\mathbf{D}) = p(\mathbf{D}) \times u(\mathbf{D}) \quad (8.9)$$

where  $w_i$  ( $\sum_{i=1}^I w_i = 1$ ) is the preference on Negotiation  $V_i$ ,  $u_i(D_i)$  is the utility of Negotiation  $V_i$  by performing Decision  $D_i$ , and  $P(V_i | pa(V_i), D_i)$  is the success rate of Negotiation  $V_i$  by considering all dependent negotiations and Decision  $D_i$ . Then the optimal policy for a MNID is defined as follows:

$$\pi = \arg \max_{\mathbf{D}} (EU(\mathbf{D})) \quad (8.10)$$

$D_i$	$p(\mathbf{D})$	$u(\mathbf{D})$
$a$	$1 \times \prod_{j=1, j \neq i}^I P(V_j   pa(V_j), D_j)$	$u_{i,b} \times w_i + \sum_{j=1, j \neq i}^I u_j(D_j) \times w_j$
$r$	$p_i \times \prod_{j=1, j \neq i}^I P(V_j   pa(V_j), D_j)$	$\Phi_i(t) \times w_i + \sum_{j=1, j \neq i}^I u_j(D_j) \times w_j$
$q$	$0 \times \prod_{j=1, j \neq i}^I P(V_j   pa(V_j), D_j)$	$0 \times w_i + \sum_{j=1, j \neq i}^I u_j(D_j) \times w_j$

Table 8.1: The joint probability and utility for a general MNID.

### 8.3.2 Four Typical Cases in a MNID

In this subsection, we discuss four typical cases in a MNID. In Table 8.1, the joint success rate and the joint utility for a MNID in different Decision  $D_i$  are listed, where  $u_{i,b}$  is the best utility gained in Negotiation  $V_i$  from opponents.

**Case 1:**  $D_1 = \dots = D_i \dots = D_I = a$

When an agent chooses to *accept* the best offer from opponents for all negotiations, ie.  $D_1 = \dots = D_i \dots = D_I = a$ , then the expected utility is:

$$\begin{aligned}
 & EU(a, \dots, a, \dots, a) \\
 &= \prod_{i=1}^I P(V_i | pa(V_i), a) \times U(a, \dots, a, \dots, a) \\
 &= \sum_{i=1}^I u_{i,b} \times w_i
 \end{aligned} \tag{8.11}$$

Equation 8.11 indicates that if an agent makes a decision to *accept* opponents' offers for all negotiations, the expected utility for a MNID is the weighted sum of utilities for all negotiations.

**Case 2:**  $D_1 = \dots = D_i \dots = D_I = r$

If an agent chooses to *reject* offers from opponents for all negotiations in a MNN, then the expected utility is:

Cases	$\Phi_i(t) = u_{i,s}$	$\Phi_i(t) = 1$
$I = 1, S_1 = 1$	$u_{1,1}$	$1 - (1 - u_{1,1})^{\tau_1 - t}$
$I = 1, S_1 > 1$	$u_{1,s}$	$1 - (\prod_{s=1}^{S_1} (1 - u_{1,s}))^{\tau_1 - t}$
$I > 1, S_i = 1$	$\sum_{i=1}^I u_{i,1} \times w_j$	$\prod_{i=1}^I (1 - (1 - u_{i,1})^{\tau_i - t})$
$I > 1, S_i > 1$	$\sum_{i=1}^I u_{i,s} \times w_j$	$\prod_{i=1}^I (1 - \prod_{s=1}^{S_i} (1 - u_{i,s})^{\tau_i - t})$

Table 8.2: Expected utilities in typical cases.

$$\begin{aligned}
& EU(r, \dots, r, \dots, r) \tag{8.12} \\
&= \prod_{i=1}^I P(V_i | pa(V_i), r) \times U(r, \dots, r, \dots, r) \\
&= \prod_{i=1}^I p_i \times \sum_{i=1}^I (\Phi_i(t) w_i) \\
&= \prod_{i=1}^I \left( 1 - \left( \frac{\prod_{s=1}^{S_i} (\Phi_i(t) - u_{i,s})}{(\Phi_i(t) - u_{i,w})^{S_i}} \right)^{\tau_i - t} \right) \times \sum_{i=1}^I (\Phi_i(t) \times w_i)
\end{aligned}$$

where  $\tau_i$  is the deadline for Negotiation  $V_i$ ,  $\Phi_i(t)$  is the utility for Negotiation  $V_i$  at time  $t$ , and  $u_{i,w}$  is the worst possible utility for Negotiation  $V_i$ .

Equation 8.12 indicates that if an agent decides to *reject* offers from its all opponents and sends out a counter-offer for each negotiation, the expected utility is impacted by the number of negotiations ( $I$ ) and the number of opponents in each negotiation ( $S_i$ ). In Table 8.2, we list the expected utility in four cases for different  $I$  and  $S_i$ . The second column indicates the expected utility when an agent sends out its worst counter-offer  $\Phi_i(t) = u_{i,b}$ , (where  $u_{i,b}$  is the best offer that the agent receives from opponents in Negotiation  $V_i$ ). The last column indicates the situation when an agent sends out its best counter-offer  $\Phi_i(t) = 1$ . Usually,  $\Phi_i(t)$  is between these two extreme values (i.e.  $\Phi_i(t) \in [u_{i,s}, 1]$ ). The agent will reject offer  $u_{i,s}$  from opponents for Negotiation  $V_i$  if and only if the counter-offer  $\Phi_i(t)$  can bring more expected utility than  $u_{i,s}$ ,  $\Phi_i(t) > u_{i,s}$ .

### Case 3: situations between Case 1 and Case 2

Besides the two extreme situations listed in Case 1 and Case 2, an agent may choose to *accept* some negotiations and to *reject* others. Let set  $\mathbf{D}^a$  be negotiations which the agent decides to accept, and set  $\mathbf{D}^r$  be negotiations

which the agent decides to reject, then  $\mathbf{D}^a \cup \mathbf{D}^r = \mathbf{D}$  and  $\mathbf{D}^a \cap \mathbf{D}^r = \emptyset$ . The expected utility can be calculated as

$$\begin{aligned}
 & EU(\mathbf{D}^a, \mathbf{D}^r) \tag{8.13} \\
 &= \prod_{D_j \in \mathbf{D}^a} P(V_j | pa(V_j), D_j) \times \prod_{D_i \in \mathbf{D}^r} P(V_i | pa(V_i), D_i) \times \\
 & \quad U(\mathbf{D}^a, \mathbf{D}^r) \\
 &= \prod_{D_i \in \mathbf{D}^r} (1 - (\frac{\prod_{s=1}^{S_i} (\Phi_i(t) - u_{i,s})}{(\Phi_i(t) - u_{i,w})^{S_i}})^{\tau_i - t}) \times \\
 & \quad (\sum_{D_j \in \mathbf{D}^a} u_{j,b} \times w_j + \sum_{D_i \in \mathbf{D}^r} \Phi_i(t) \times w_i)
 \end{aligned}$$

Equation 8.13 indicates that an agent decides to accept some negotiations and to reject the others. In order to calculate the expected utility, the joint success rates and the joint utilities for accepted negotiations and rejected negotiations should be calculated separately, and then combined together.

**Case 4:**  $D_1 = q$  or  $\dots D_i = q$  or  $\dots D_I = q$

If an agent chooses to *quit* from a negotiation, such as Negotiation  $V_i$ , then the expected utility is:

$$\begin{aligned}
 & EU(D_1, \dots, q, \dots, D_I) \tag{8.14} \\
 &= 0 \times \prod_{j=1, j \neq i}^I P(V_j | pa(V_j), D_j) \times U(D_1, \dots, q, \dots, D_i) \\
 &= 0
 \end{aligned}$$

Equation 8.14 indicates that if an agent chooses to *quit* from Negotiation  $V_i$ , then the expected utility for a MNID is 0. That is because all negotiations in a MNN are related and a failure of any negotiation in a MNN will lead to a failure to achieve the global goal of negotiations. For instance, an agent has two related negotiations, ie. a mortgage negotiation between several bankers and a property negotiation between several real estate agents. If the agent fails any negotiation, then the global goal of these two negotiations, ie. ‘to purchase



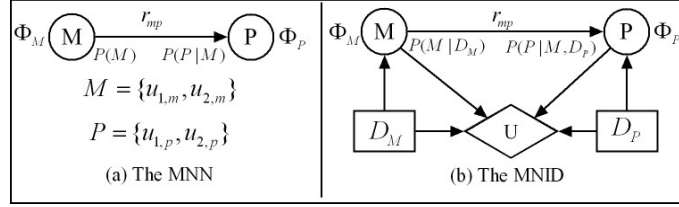


Figure 8.4: The MNN and MNID for the experiment.

a property by using a mortgage', definitely cannot be achieved. So when an agent chooses to quit from any negotiation, the expected utility decreases to 0.

## 8.4 Experiment

The experimental results of the proposed approach, together with a performance comparison with the NDF approach [FSJ98] are reported in this section .

### 8.4.1 Experiment Setup

Suppose that Agent  $b$ 's global goal is to get a mortgage and to purchase a property with the mortgage, so Agent  $b$  needs to perform two negotiations. The first negotiation, (*mortgage negotiation*), is processed between Agent  $b$  and two bankers (Opponents  $o_{m1}, o_{m2}$ ) on the issues of mortgage amount and interest rate. The second negotiation, (*property negotiation*), is processed between Agent  $b$  and two real estate agents (Opponents  $o_{p1}, o_{p2}$  or Opponents  $o_{p3}, o_{p4}$ ) on the issue of property price. It is assumed that Agent  $b$  believes that the *property negotiation* depends on the result of the *mortgage negotiation*. In Figure 8.4, the MNN and MNID for Agent  $b$  are displayed. Circle nodes  $M$  and  $P$  indicate the *mortgage negotiation* and the *property negotiation*, respectively. Rectangular nodes  $D_M$  and  $D_P$  are decisions on two negotiations, respectively. Diamond node  $U$  is the joint utility of the MNID. We adopt equal weighting between these two negotiations, so  $w_m = w_p = 0.5$ . Because Agent  $b$  cannot afford a property price which is higher than the mortgage amount, the restriction from *mortgage negotiation* to *property negotiation* is  $r_{mp}$ , which indicates that 'the reserved property price is the mortgage amount'. Negotiation parameters for the two negotiations are listed in Table 8.3 and Table 8.4, respectively. Because *mortgage negotiation* contains two issues, (i.e. mortgage amount and interest rate),

Agent	Initial Offer	Reserved Offer	Deadline
Agent $b$	(500k, 5%)	(300k, 7%)	10
Opponent $o_{m1}$	(310k, 6.9%)	(450k, 5.2%)	15
Opponent $o_{m2}$	(330k, 6.5%)	(500k, 5.5%)	9

Table 8.3: Parameters for mortgage negotiation.

Agent	Initial Offer	Reserved Offer	Deadline
Agent $b$	200k	depends	12
Opponent $o_{p1}$	550k	330k	15
Opponent $o_{p2}$	500k	350k	9
Opponent $o_{p3}$	650k	450k	10
Opponent $o_{p4}$	630k	470k	11

Table 8.4: Parameters for property negotiation.

we adopt the *package deal procedure* [FWJ06a] for this multi-issue negotiation and equally weight the two issues. We demonstrate experimental results in two scenarios, ie. a successful scenario, (Scenario A) and an unsuccessful scenario, (Scenario B). In Scenario A, Agent  $b$  negotiates with Opponents  $o_{m1}$ ,  $o_{m2}$ ,  $o_{p1}$  and  $o_{p2}$ , while in Scenario B, Agent  $b$  negotiates with Opponents  $o_{m1}$ ,  $o_{m2}$ ,  $o_{p3}$  and  $o_{p4}$ .

#### 8.4.2 Scenario A (a successful scenario)

In Scenario A, Agent  $b$  negotiates with Opponents  $o_{m1}$  and  $o_{m2}$  for *mortgage negotiation*, (the first negotiation) and with Opponents  $o_{p1}$  and  $o_{p2}$  for *property negotiation*, (the second negotiation). Firstly, we adopt the NDF approach to sequentially process *mortgage negotiation* and *property negotiation* and the outcomes of the two negotiations are illustrated in Figures 8.5 and 8.6, respectively. Let letter  $a$  indicate *accept*, letter  $r$  indicate *reject* and letter  $u$  indicate utility. The legend  $u1a$  (or  $u2a$ ) indicates the utility of the first (or second) negotiation by accepting opponents' offers, and legend  $u1r$  (or  $u2r$ ) indicates the utility of the first (or second) negotiation by sending a counter-offer. In Scenario A, both negotiations successfully reached an agreement by adopting the NDF negotiation model. The utility of *mortgage negotiation* is 0.5, and the mortgage amount is \$405,556. Then the amount \$405,556 is used as Agent  $b$ 's reserved price in *property negotiation*. The utility for *property negotiation* is 0.19. Because these two negotiations are equally weighted, the overall utility is 0.35.

The negotiation outcomes of the proposed approach are illustrated in Figures 8.7

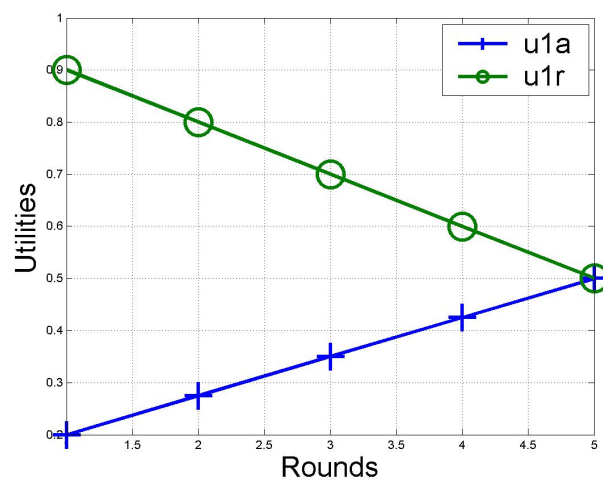


Figure 8.5: Mortgage negotiation using NDF approach for Scenario A.

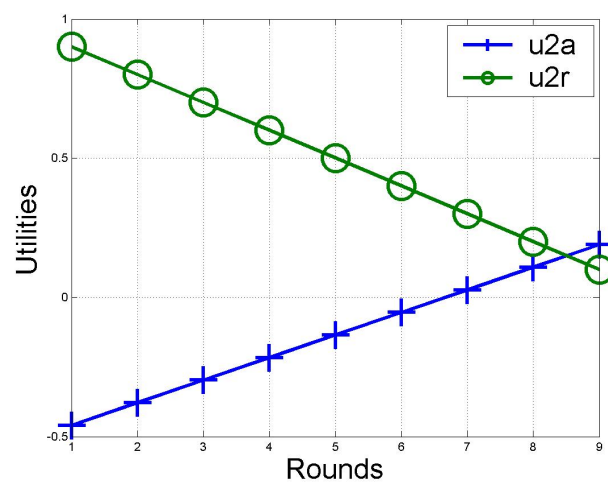


Figure 8.6: Property negotiations using NDF approach for Scenario A.

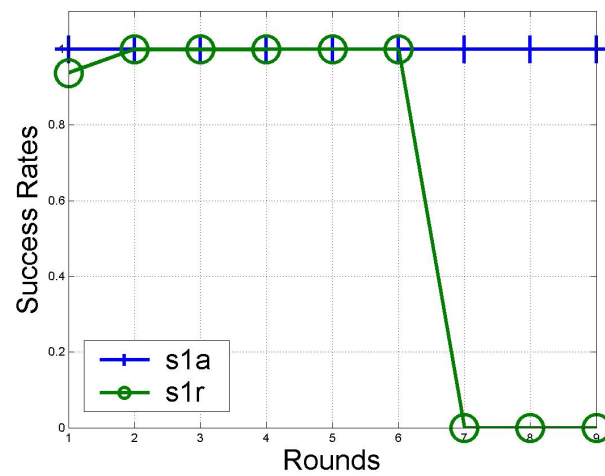


Figure 8.7: Success rate of mortgage negotiation for Scenario A.

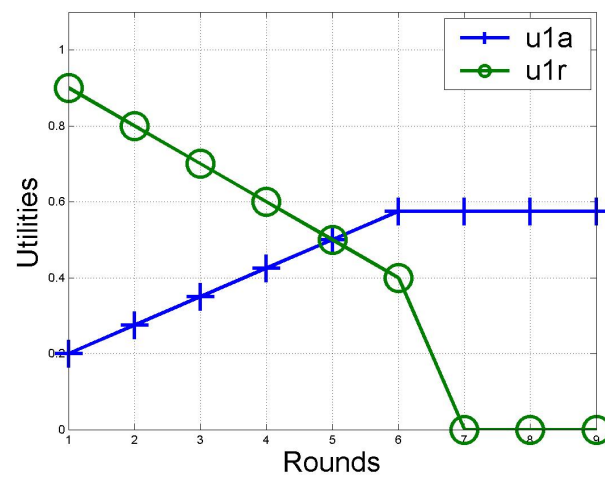


Figure 8.8: Utility of mortgage negotiation for Scenario A.

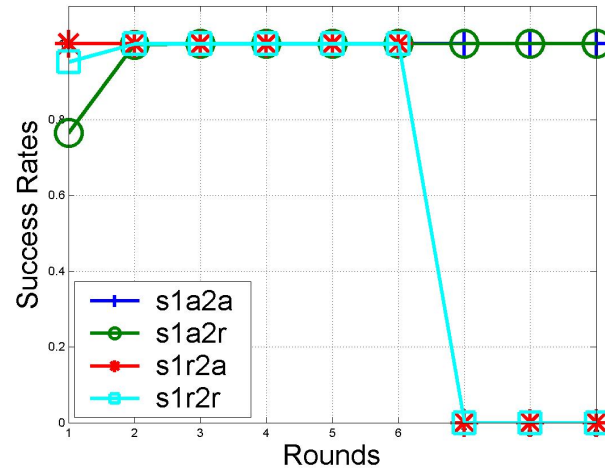


Figure 8.9: Success rate of property negotiation for Scenario A.

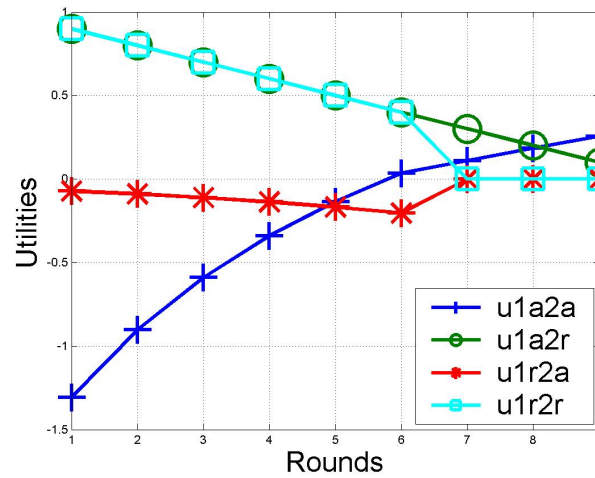


Figure 8.10: Utility of property negotiation for Scenario A.

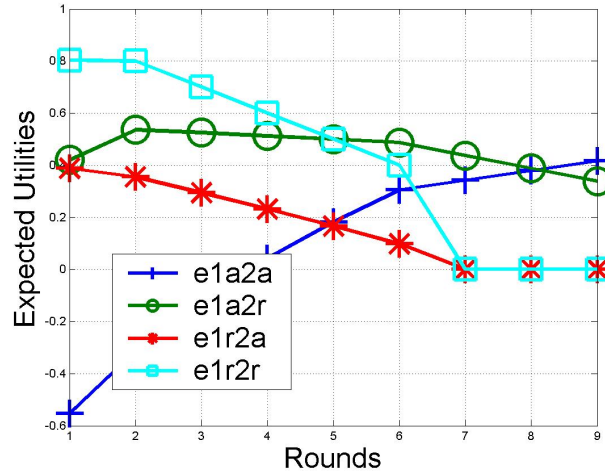


Figure 8.11: Expected utilities for both mortgage and property negotiation for Scenario A.

through 8.10. By adopting the MNN and MNID, *mortgage negotiation* and *property negotiation* are synchronously processed. Agent *b*'s reserved price in *property negotiation* is dynamically updated in each negotiation round according to the latest offer from *mortgage negotiation*. The success rate and utility for mortgage negotiation are illustrated in Figures 8.7 and 8.8, respectively. The success rate and utility for *property negotiation* are illustrated in Figures 8.9 and 8.10, respectively. Let letter *s* indicate success rate and letter *e* indicate expected utility. For instance, Legend *s1r2a* indicates the success rate of the MNID by rejecting all opponents' offers in *mortgage negotiation* and accepting the best offer from opponents in *property negotiation*, and Legend *e1a2r* indicates the expected utility of the MNID by accepting the best offer from opponents in *mortgage negotiation* and rejecting all opponents' offers in *property negotiation*.

The expected utility for the MNID is illustrated in Figure 8.11. It can be seen that before round-6, curve *e1r2r* leads to the highest expected utility; from round-6 to round-8, curve *e1a2r* leads to the highest expected utility; after round-8, curve *e1a2a* leads to the highest expected utility. Therefore, in order to maximize the outcome of the MNID, Agent *b* should reject all opponents' offers in both negotiations in the first five rounds. At round-6, Agent *b* should accept the best offer from opponents in *mortgage negotiation* but keep on bargaining in *property negotiation* until round-8. At round-9, Agent *b* should accept the best offer in *property negotiation*. By adopting such a decision policy, the utility of *mortgage negotiation* increases to

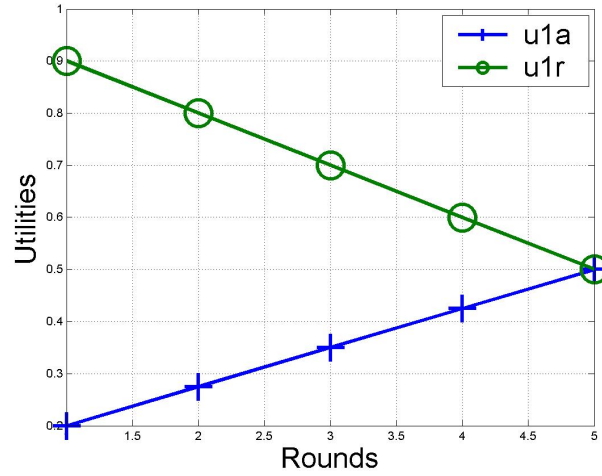


Figure 8.12: Mortgage negotiation using NDF approach for Scenario B.

0.58 and the utility of *property negotiation* increases to 0.26, so the global utility is increased to 0.42, which is 20% more than the result from the NDF approach.

The result of Scenario *A* indicates that if the global goal of related negotiations can be achieved, the proposed approach can improve the negotiation outcome through considering both joint success rate and joint utility. By comparison with the sequential negotiation processes, the proposed approach can synchronously process all related negotiations and dynamically optimize the global outcome.

### 8.4.3 Scenario B (an unsuccessful scenario)

In Scenario *B*, Agent *b* negotiates with Opponents  $o_{m1}$  and  $o_{m2}$  in *mortgage negotiation* and with Opponents  $o_{p3}$  and  $o_{p4}$  in *property negotiation*. Also, we adopt the NDF approach to sequentially process *mortgage negotiation* and *property negotiation*. The outcomes of the two negotiations are illustrated in Figures 8.12 and 8.13, respectively. In contrast to Scenario *A*, Agent *b* successfully completes *mortgage negotiation*, but fails *property negotiation*. In this case, the result of *mortgage negotiation* is meaningless or even has a negative impact by considering the global goal of related negotiations. That is because without purchasing a property, the approval of a mortgage proposal can only lead to an unnecessary cost on mortgage interest and a penalty from the bank. Therefore, if Agent *b* is not absolutely sure that the global goal of its related negotiations can be finally achieved, it is not efficient to process these negotiations sequentially.

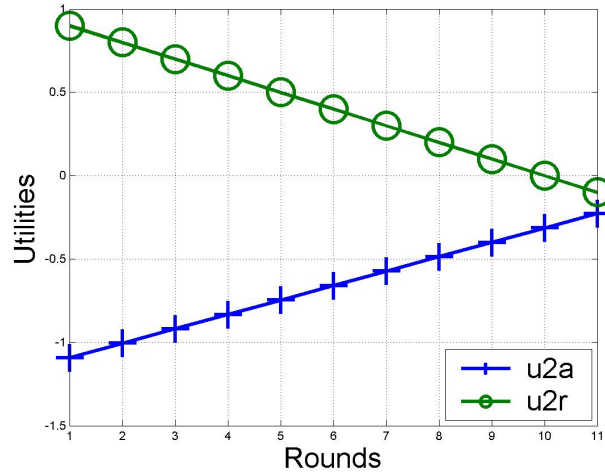


Figure 8.13: Mortgage negotiation using NDF approach for Scenario B.

However, if we employ the proposed approach for Scenario *B*, the outcome is different. In Figures 8.14 and 8.18, we illustrate the experimental results by adopting the proposed approach. In order to avoid partially reaching the global goal, Agent *b* can only select policies between curves  $e1a2a$  and  $e1r2r$  (see Figure 8.18), which means accepting or rejecting both negotiations together. It can be seen that before round-8, curve  $e1r2r$  exceeds the curve  $e1a2a$ . At round-8, curve  $e1a2a$  can bring more utility to Agent *b* than curve  $e1r2r$ . It seems that Agent *b* can accept opponents' offers in both negotiations at round-8. However, because Agent *b* cannot purchase a property whose price is higher than the mortgage amount, so the utility *property negotiation* must be greater than 0. At round-8, by accepting the best offer from opponents, Agent *b* will lose utility by 0.17 (see Figure 8.17), so Agent *b* cannot reach agreement in both negotiations at round-8. However, if Agent *b* stays on curve  $e1r2r$  at round-8, the expected utility will be a negative number as well in round-9. Therefore, in order to avoid any loss, Agent *b* cannot choose either to accept or to reject both negotiations at round-8, but must quit from negotiations without achieving any agreement with any opponent. So Agent *b* does not need to worry about the unnecessary interest and the penalty from the bank anymore. The results of Scenario *B* indicate that if the global goal of related negotiations cannot be achieved, then the proposed approach can help agents to avoid unnecessary losses caused by the sequential procedure.



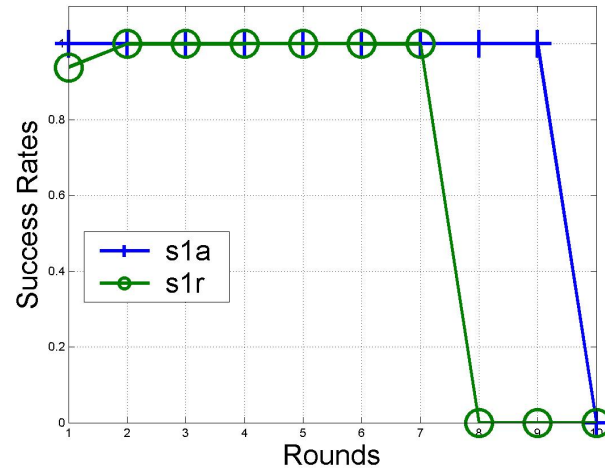


Figure 8.14: Success rate of mortgage negotiation for Scenario B.

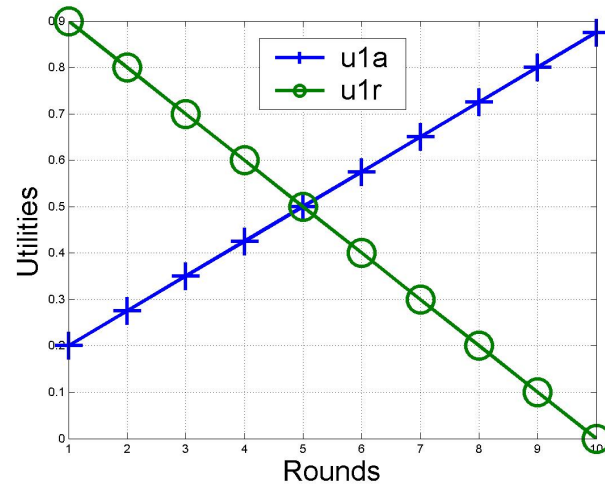


Figure 8.15: Utility of mortgage negotiation for Scenario B.

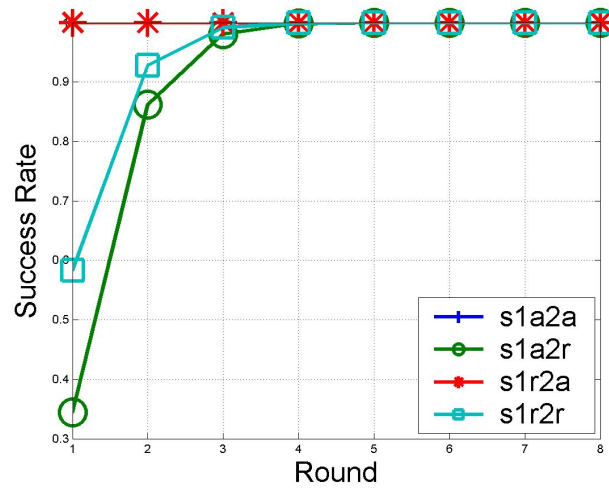


Figure 8.16: Success rate of property negotiation for Scenario B.

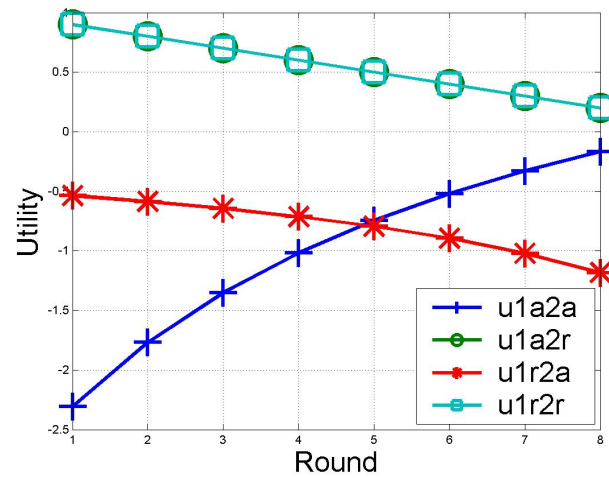


Figure 8.17: Utility of property negotiation for Scenario B.

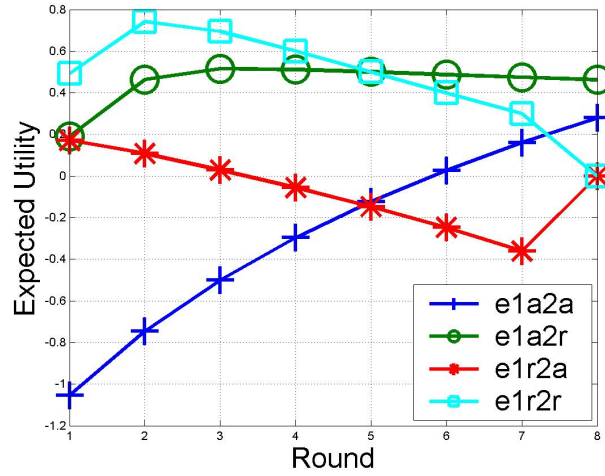


Figure 8.18: Expected utilities for both mortgage and property negotiation for Scenario B.

## 8.5 Summary

In this chapter, we proposed a Multi-Negotiation Network (MNN) and a Multi-Negotiation Influence Diagram (MNID) to handle multiple related negotiations in a multi-agent system. In the real world, an agent may need to process several related negotiations in order to reach a global goal. Most state-of-the-art approaches perform these related negotiations sequentially. However, because the result of the latter negotiation is not predictable by using a sequential procedure, agents cannot optimally execute all negotiations in correct sequential order. In some cases, when the global goal cannot be reached, the former performed negotiations may become meaningless and agreements on these negotiations may lead to unnecessary losses. The motivation of our approach is to solve such a problem and handle multiple related negotiations concurrently. Firstly, the joint success rate and the joint utility by considering all related negotiations are calculated dynamically based on a MNN. Secondly, by employing a MNID, an agent's possible decisions on each negotiation are considered and reflected by the value of an expected utility. Lastly, through comparing expected utilities between all possible policies, an optimal policy is generated to optimize the global outcome of multiple related negotiations. The experimental results indicate that the proposed approach can improve an agent's global utility of multiple related negotiations in a successful end scenario, and avoid unnecessary losses for the agent in an unsuccessful end scenario.

# Chapter 9

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## Conclusion and Future Work

Agent negotiation is one of the major issues of both research and application in multi-agent systems. The remarkable growth of MAS applications in open and dynamic environments brings higher requirements and more challenges to agent negotiation. In recognizing these challenges, this thesis deeply investigated agent negotiation problems, and proposed agent negotiation approaches based on three negotiation levels. In this chapter, the major contributions of this thesis are summarized and future work on this research is outlined.

### 9.1 Summary of Major Contributions

In this thesis, we have presented a personal view of agent negotiation through both *agent setting* and *environment setting*, and classified agent negotiation into three hierarchical levels based on the complexity of *environment setting*. We have discussed the challenges and research issues in agent negotiation at the present time based on our classification. The major contribution of this thesis is to develop agent negotiation approaches on each level of the proposed hierarchical classification.

- Contributions on the *Bilateral Level*
  - Bilateral single issue negotiation is a fundamental research problem in agent negotiation. In Chapter 3, a regression-based prediction approach was proposed to estimate agent behaviors in single issue negotiation. Three regression functions, i.e. a linear function, a power function and a quadratic function, were introduced to predict agent behavior in different situations. It was shown that the proposed prediction approach could estimate agent negotiation behaviors accurately and efficiently. This prediction approach overcomes the major limitation of the most existing

prediction approaches, i.e. only needing the historical record of the current negotiation without a pre-training process.

- Chapter 4 studied the research issue of optimal negotiation outcome on bilateral multi-issue negotiation, which is one of the most active research issues in current agent negotiation studies. Based on the agent behavior prediction approach proposed in Chapter 3, an agent preference prediction approach is proposed. Firstly, through observing an agent’s counter-offers, the agent’s negotiation behavior on each single issue was estimated. Secondly, through analyzing the differences between the agent’s negotiation behaviors throughout all issues, the agent’s preference could be predicted as well. Lastly, two optimal offer generation approaches were proposed to search for the bi-beneficial negotiation outcome based on the predicted preference. It was shown that the proposed preference prediction approach and the optimal offer generation approaches could estimate an agent’s preference and lead to a ‘win-win’ negotiation outcome efficiently and effectively in bilateral multi-issue negotiation.

- Contributions on the *Multilateral Level*

- Chapter 5 studied the research issue of partner selection in multilateral negotiation. Usually, a multilateral negotiation contains many participants, and it will be inefficient for an agent to perform a sophisticated negotiation with each potential partner, especially when negotiation environments become open and dynamic. Linear and non-linear partner selection approaches were proposed in this chapter to filter out unqualified partners before negotiations start, so agents can pay more concern to partners with a high likelihood to reach an agreement; the efficiency and effectiveness of multilateral negotiations were also improved.
- Chapter 6 extended the market-driven based negotiation model from static negotiation environments to dynamic environments. Four concession factors in MDAs (namely *trading opportunity*, *trading competition*, *trading time and strategy* and *eagerness*) are modified by taking into account uncertain and dynamic outside options. In the extended market-driven negotiation model, agents are allowed to enter or leave an ongoing

negotiation freely. Agents will notice the changes of negotiation environments, and update their concession strategies dynamically in order to increase their negotiation outcomes and success rates. It was shown that the extended model successfully reflected the dynamic changes of negotiation environments, and modified agents negotiation strategies efficiently.

- Chapter 7 studied multi-issue negotiation by considering dynamic environments. The major differences between single issue negotiation and multi-issue negotiation are that: (1) multi-issue negotiation between intelligent agents can lead negotiators to ‘win-win’ negotiation outcomes, which can hardly be achieved by single issue negotiation; and (2) multi-issue negotiation can process multiple issues synchronously. In this chapter, we proposed a market-based multi-issue negotiation model by considering the uncertainty of negotiation environments, the uncertainty of negotiators, and non-linear preferences. It was shown that the proposed approaches can successfully capture the dynamic changes of negotiation environments, and modify agents’ negotiation strategies. Also, the multiple offers strategies successfully increased agents’ negotiation outcomes and success rates in complex environments.

- Contributions on the *Multi-Negotiation Level*

- Multiple related negotiation is a new research issue in the area of agent negotiations, and has not been studied deeply in the literature. Chapter 8 proposed a Multi-Negotiation Network and a Multi-Negotiation Influence Diagram to dynamically represent the dependency relationships among multiple negotiations, and tried to search for an optimal execution policy to perform the related negotiations concurrently and optimally. It was shown that the proposed approaches can successfully improve an agent’s global utility of multiple related negotiation in a successful end scenario, and avoid unnecessary losses for the agent in an unsuccessful end scenario.

## 9.2 Future Work

This research can be extended by engaging in investigations focussing on the following aspects.

- Chapter 3 proposed an agent behavior prediction approach to estimate possible agent negotiation behavior by analyzing their historical negotiation records. However, the proposed approach only focused on agents with linear utility functions, and cannot handle cases when agents employ non-linear utility functions. In the future, the current approach could be extended from linear domains to non-linear domains.
- Chapter 4 proposed an agent preference prediction approach, as well as computational approaches for mutually beneficial negotiation outcomes in bilateral multi-issue negotiation. Currently, the non-linear preferences are temporarily not considered. Future work on this research may focus on multi-issue negotiation with non-linear preferences.
- Chapter 5 proposed partner selection mechanisms by employing both linear and non-linear approaches. Further, the proposed approaches can be employed in both cooperative and competitive negotiation environments. Future work on this research could pay attention to extend our current work by using trust-based and/or reputation-based technologies, so as to produce a more comprehensive evaluation on partners.
- Chapter 6 extended the market-driven negotiation model from a static negotiation environment to a dynamic negotiation environment by considering changes of outside options. Currently, consideration of future possible changes of the negotiation environment is based on the assumption that all negotiators will have the same probability to enter or leave a negotiation. In real world applications, such an assumption is not always true. Therefore, our future work on this research will take each agent's individual situation into account when possible changes of negotiation environment need to be predicted.
- Chapter 7 proposed a market-based negotiation model in considering multilateral negotiators, multiple issues, multiple non-linear preferences, and a dynamic environment. Future work on this research could focus on searching for the optimal bi-beneficial negotiation outcome in dynamic environments.
- Chapter 8 proposed a Multi-Negotiation Network and a Multi-Negotiation Influence Diagram to handle multiple related negotiations concurrently and

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optimally in dynamic environments. At the present time, only two dependency relationships between negotiations are considered. Future work on this research may pay attention to generating a comprehensive model to express the dependency relationships between multiple negotiations.



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